PB83-253500

Characteristics of an Asbestos Exposure Assessment Algorithm

Research Triangle Inst.
Research Triangle Park, NC

Prepared for

Environmental Protection Agency, Washington, DC

Jul 81

U.S. Department of Commerce
National Technical Information Service
NTIS

TECHNICAL REPORT DATA
(Please read Instructions on the reverse before completing)

1. REPORT NO.	2.	3. RECIPIENT'S ACCESSION NO.
EPA 560/5-81-5		PB83 253500

4. TITLE AND SUBTITLE	5. REPORT DATE
Characteristics of an Asbestos Exposure Assessment Algorithm	July 1981
	6. PERFORMING ORGANIZATION CODE
7. AUTHOR(S)	8. PERFORMING ORGANIZATION REPORT NO.
Everett Logue, Tyler Hartwell	
9. PERFORMING ORGANIZATION NAME AND ADDRESS	10. PROGRAM ELEMENT NO.
Research Triangle Institute Post Office Box 12194 Research Triangle Park, North Carolina 27709	11. CONTRACT/GRANT NO.
12. SPONSORING AGENCY NAME AND ADDRESS	13. TYPE OF REPORT AND PERIOD COVERED
Environmental Protection Agency Office of Pesticides and Toxic Substances Washington, D.C. 20460	14. SPONSORING AGENCY CODE

15. SUPPLEMENTARY NOTES

16. ABSTRACT

This report describes the characteristics of a proposed asbestos exposure assessment algorithm. Algorithm variable distributions are presented along with correlations between various algorithm variables in different locations (e.g., New York City, North Carolina and Montgomery County, Ohio). Available data are analyzed and discussed from the perspective of the algorithm's measurement reliability and validity. It is concluded that the algorithm's reliability and validity cannot be estimated from the available data. However, additional research may lead to the development of an acceptably valid, airborne-asbestos-level surrogate. This yet-to-be developed surrogate exposure index could be used to help State and local officials identify and control asbestos exposures in schools.

17. KEY WORDS AND DOCUMENT ANALYSIS

a. DESCRIPTORS	b. IDENTIFIERS/OPEN ENDED TERMS	c. COSATI Field/Group
Asbestos Exposure Algorithm Asbestos Airborne Levels Asbestos in Bulk Samples Asbestos Algorithm Scores in Schools Statistical Analysis		

18. DISTRIBUTION STATEMENT	19. SECURITY CLASS *(This Report)*	21. NO. OF PAGES
		70
	20. SECURITY CLASS *(This page)*	22. PRICE

EPA Form 2220-1 (Rev. 4-77) PREVIOUS EDITION IS OBSOLETE

United States
Environmental Protection
Agency

Toxic Substances
Washington, DC 20460

EPA-560/5-81-5
July 1981

Toxic Substances

PB83-253500

EPA

Characteristics of an Asbestos Exposure Assessment Algorithm

REPRODUCED BY
NATIONAL TECHNICAL
INFORMATION SERVICE
U.S. DEPARTMENT OF COMMERCE
SPRINGFIELD, VA 22161

EPA 560/5-81-5
July 1981

CHARACTERISTICS OF AN ASBESTOS EXPOSURE ASSESSMENT ALGORITHM

by

Everett E. Logue
Tyler D. Hartwell

Research Triangle Institute
Research Triangle Park,
North Carolina 27709

EPA Contract Number 68-01-5848

Task Manager: Cindy Stroup
Project Officer: Joe Carra

Design and Development Branch
Exposure Evaluation Division
Office of Toxic Substances
Washington, DC 20460

OFFICE OF PESTICIDES AND TOXIC SUBSTANCES
U.S. ENVIRONMENTAL PROTECTION AGENCY
WASHINGTON, DC 20460

DISCLAIMER NOTICE

This report was prepared under contract to an agency of the United States Government. Neither the United States Government nor any of its employees, contractors, subcontractors, or their employees, makes any legal liability or responsibility for any third party's use or the results of such use of any information, apparatus, product or process disclosed in this report, nor represents that its use by such third party would not infringe privately-owned rights.

Publication of the data in this document does not signify that the contents necessarily reflect the joint or separate views and policies of each sponsoring agency. Mention of trade names or commercial products does not constitute endorsement or recommendation for use.

TABLE OF CONTENTS

		Page
DISCLAIMER		ii
TABLE OF CONTENTS		iii
LIST OF FIGURES		v
LIST OF TABLES		vi
ACKNOWLEDGEMENTS		viii
ABSTRACT		ix
I.	INTRODUCTION	1
II.	DATA AVAILABLE FOR STATISTICAL ANALYSIS	3
III.	DATA COLLECTION METHODS	5
IV.	VARIABLE DISTRIBUTIONS	7
	A. Basic Features of the Algorithm Data	7
	B. Comparisons Between Algorithm Variable Distributions in Different Locations	12
	C. Algorithm Score Distributions	18
	D. Asbestos Air Level Distribution	25
V.	CORRELATIONS BETWEEN ALGORITHM VARIABLES	30
	A. Introduction	30
	B. Correlations Involving Material Condition	33
	C. Correlations Involving Water Damage	34
	D. Correlations Involving Exposed Surface	34
	E. Correlations Involving Accessibility	34
	F. Correlations Involving Activity	35
	G. Correlations Involving Air Plenum	35
	H. Correlations Involving Friability	35
	I. Correlations Involving Percent Asbestos	35
	J. School's Program Summary	36
	K. Observational Deletion Effects Upon Intercorrelations	36
	L. Acoustical Tile Deletions and Intercorrelations	38
	M. Intercorrelations in the Industrial Hygienics, the Battelle, and the Paris Datasets	40

TABLE OF CONTENTS (cont.)

		Page
VI.	CORRELATIONS BETWEEN THE SCORE AND ITS COMPONENTS	42
	A. School Programs Data	42
	B. Friability	44
	C. Percent Asbestos	44
	D. Acoustical Tile Deletion Effects	45
	E. Correlations in the Industrial Hygienics, the Battelle, and the Paris Datasets	45
VII.	RELATIONSHIPS BETWEEN THE ALGORITHM VARIABLES AND VARIOUS DEPENDENT VARIABLES	48
	A. School Programs Data	48
	B. North Carolina Data	55
	C. Montgomery County Data	55
	D. New York City Data	56
	E. Battelle Data	56
	F. Comments Concerning the Multivariable Analyses	56
	G. Plots Characterizing the Relationship Between the Score and Asbestos Air Level Data	57
VIII.	CONCLUSIONS	65
	A. Variable Distribution Summary	65
	B. Algorithm Variable Intercorrelation Summary	66
	C. Score/Component Correlation Summary	66
	D. Algorithm Variable--Dependent Variable Summary	66
	E. Algorithm Score--Airborne Asbestos Summary	67
	F. General Comments	67
REFERENCES		69
Appendix A:	Components of the Potential Exposure Score	A-1

LIST OF FIGURES

No.		Page
1	Plot of Mean Fiber Concentrations (Determined by Phase Contrast Microscopy) Versus The Asbestos Algorithm Score: Industrial Hygienics Dataset	58
2	Plot of Air Chrysotile Levels (ACl) versus the Asbestos Algorithm Score (SCORE).: Paris Dataset.	59
3	Plot of LOG_e (Air Chrysotile Levels), (LAIR) versus LOG_e (Asbestos Algorithm Score), (LSCORE): Paris Dataset.	60
4	Plot of Stimulated Fiber-Releasability (VAIR) versus the Asbestos Algorithm Score (SCORE): Battelle Dataset	61
5	Plot of LOG_e (Stimulated Fiber-Releasability), (LAIR), versus LOG_e (Asbestos Algorithm Score), (LSCORE): Battelle Dataset. . . .	62
6	Plot of Stimulated Fiber-Releasability (VAIR) versus the Modified Algorithm Score (SCOR2): Battelle Dataset	63
7	Plot of LOG_e (Stimulated Fiber-Releasability), (LAIR), versus LOG_e (Modified Algorithm Score), (LSCORE2): Battelle Dataset . . .	64

LIST OF TABLES

No.		Page
1	DISTRIBUTION OF SCHOOL ASBESTOS ALGORITHM VARIABLES	8
2	DISTRIBUTIONS OF SCHOOL ASBESTOS ALGORITHM VARIABLES: CERTAIN OBSERVATIONS DELETED.	10
3	DISTRIBUTIONS OF SCHOOL ASBESTOS ALGORITHM VARIABLES: ACOUSTICAL TILE OBSERVATIONS DELETED.	13
4	ALGORITHM DATA COLLECTED BY INDUSTRIAL HYGIENICS, INC. IN NORTHEASTERN PUBLIC BUILDINGS	14
5	DISTRIBUTIONS OF SCHOOL ASBESTOS ALGORITHM VARIABLES.	15
5A	MOST FREQUENTLY USED ALGORITHM VARIABLE CODES	17
6	DISTRIBUTIONS OF ASBESTOS ALGORITHM SCORES.	19
7	DISTRIBUTIONS OF ASBESTOS ALGORITHM SCORES: CERTAIN OBSERVATIONS DELETED.	21
8	DISTRIBUTIONS OF ASBESTOS ALGORITHM SCORES: ACOUSTICAL TILE OBSERVATIONS DELETED	22
9	DISTRIBUTION OF THE ALGORITHM SCORE DATA COLLECTED BY INDUSTRIAL HYGIENICS, INC. IN THE NORTHEAST	23
10	DISTRIBUTIONS OF ASBESTOS ALGORITHM SCORES.	24
11	DISTRIBUTION OF SCOR2	26
12	DISTRIBUTION OF THE ASBESTOS AIR LEVEL DATA COLLECTED BY INDUSTRIAL HYGIENICS, INC. IN THE NORTHEAST	27
13	DISTRIBUTION OF STIMULATED FIBER-RELEASABILITY MEASUREMENTS . .	28
14	DISTRIBUTION OF CHRYSOTILE TEM AIR LEVEL MEASUREMENTS	29
15	SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM VARIABLES	31
16	SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM VARIABLES: CERTAIN OBSERVATIONS DELETED.	32
16A	SUMMARY OF ALGORITHM VARIABLE INTERCORRELATIONS	37

LIST OF TABLES (cont.)

No.		Page
17	SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM VARIABLES: ACOUSTICAL TILE OBSERVATIONS DELETED	39
18	SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM VARIABLES	41
19	SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM SCORES AND THE EIGHT COMPONENTS OF THE SCORES	43
20	SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM SCORES AND THE EIGHT COMPONENTS OF THE SCORES: ACOUSTICAL TILE OBSERVATIONS DELETED	46
21	SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM SCORES AND THE EIGHT COMPONENTS OF THE SCORES	47
22	DISCRIMINANT ANALYSES OF ASBESTOS ALGORITHM SCORES	49
23	MULTIVARIABLE MODELS WITH DIFFERENT DEPENDENT VARIABLES: NORTH CAROLINA FILE	51
24	MULTIVARIABLE MODELS WITH DIFFERENT DEPENDENT VARIABLES: MONTGOMERY COUNTY FILE	52
25	DISCRIMINANT ANALYSES OF MATERIAL TYPE (SOFTM): NEW YORK FILES	53
26	REGRESSION ANALYSES OF STIMULATED FIBER-RELEASABILITY MEASUREMENTS	54

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the following individuals for providing useful comments and/or data: Don Lentzen and Gene Brantley, Research Triangle Institute; Anthony Smith and Roger Chiljean, New York City Board of Education; Terry Wright, Montgomery County Health District; Cindy Stroup, Joe Breen, Larry Longanecker, and Larry Dorsey, Environmental Protection Agency; Ralph Self, North Carolina Department of Public Instruction; Pat Curran, North Carolina Division of Health Services; Bert Price, Battelle Columbus Laboratories; and James Schirripa, Industrial Hygienics.

ABSTRACT

This report describes the characteristics of a proposed asbestos exposure assessment algorithm. Algorithm variable distributions are presented along with correlations between various algorithm variables in different locations (e.g., New York City, North Carolina and Montgomery County, Ohio). Available data are analyzed and discussed from the perspective of the algorithm's measurement reliability and validity. It is concluded that the algorithm's reliability and validity cannot be estimated from the available data. However, additional research may lead to the development of an acceptably valid, airborne-asbestos-level surrogate. This yet-to-be developed surrogate exposure index could be used to help State and local officials identify and control asbestos exposures in schools.

I. INTRODUCTION

This report describes the characteristics of a proposed asbestos exposure assessment algorithm. The algorithm was developed by the Environmental Protection Agency (EPA) to help State and local officials identify and control potential asbestos exposures in schools. The asbestos-containing materials of interest in schools include soft or friable insulation or sound proofing materials usually found on the ceilings and walls of classrooms, corridors, gymnasiums, and band rooms. In some schools asbestos-containing materials were applied to structural steel to minimize building collapse during a fire. Public concern has focused upon the possible adverse health effects caused by respirable airborne asbestos released by deteriorating asbestos-containing surfacing materials.

At the international conference in 1978, Henderson and Enterline (1979) presented data supporting the existence of a strong linear relationship between total asbestos dust exposure and respiratory cancer mortality. The authors' dose-response curve suggests that men who experienced relatively high occupational asbestos exposures (33×10^6 particles/ ft^3) for 30 years also experienced a cancer risk approximately 7.5 times the risk to men in the general population. McDonald and Liddell's (1979) dose-response curve suggests that an occupational exposure of 50×10^6 particles/ft^3 for 30 years increases respiratory cancer risk approximately three-fold. In spite of the fact that different populations were studied, it is of interest that both research groups present convincing data that there is a linear relationship between cumulative dust exposure and respiratory cancer mortality.

The Environmental Protection Agency (EPA) has established a program to help State and local officials identify and control potential asbestos exposures in schools (USEPA 1979a). This program was established because of the increasing amount of data supporting the existence of a causal relationship either between asbestos exposure and serious morbidity or between asbestos exposure and respiratory cancer (Henderson and Enterline 1979, McDonald and Liddell 1979, and Berry and Lewinsohn 1979).

In a preliminary report the EPA suggests how the health risks associated with asbestos exposures in schools could be estimated by extrapolating a linear nonthreshhold model constructed from existing occupational data (US

EPA 1980b). The validity of a school-specific health risk estimate depends upon the validity of the dose-response model employed and the asbestos-exposure measurements taken in schools.

The exposure measurements most relevant to health risk estimation in schools (or occupational settings) are asbestos air-level concentrations because asbestos fibers enter the body largely through respiration. Unfortunately, the resources necessary for the collection and analysis of scientifically valid air samples in all schools, or in all schools where bulk sample analysis has confirmed the presence of friable asbestos-containing materials, are simply not available at the local, or even the national level. Hence, it is appropriate to consider measuring asbestos exposures in schools by using an asbestos air concentration surrogate.

The percentage of asbestos present in a representative bulk sample of friable suspect material could be considered a possible asbestos air concentration surrogate. Yet the EPA has recognized that the amount of asbestos present in fire proofing or acoustical materials is not the only determinant of asbestos air concentrations. In their guidance document (USEPA 1979a) they suggest that (1) the asbestos-containing material's general condition, (2) the extent of water damage, (3) the quantity of material exposed, (4) the degree of accessibility, (5) the level of human activity present, (6) the presence of air plenums, (7) the material's friability, and (8) the percentage of asbestos in the material are all important determinants of asbestos exposures in schools. In addition the EPA has considered recommending the use of an "asbestos exposure score," which summarizes information obtained from bulk sample analysis and from "walk-through" ratings of the remaining seven characteristics listed above. This asbestos exposure score or asbestos exposure algorithm is one of many asbestos air concentration surrogates which could be developed. If this asbestos exposure algorithm is to be used by local officials to guide their decisions concerning the removal, the enclosure, or the encapsulation of asbestos-containing materials, then the algorithm should have a reasonable degree of measurement reliability and validity.

The EPA has recognized the importance of studying the properties of asbestos air concentration surrogates. Patton et al. (1980), under contract to the EPA, collected and analyzed data concerning the consistency or inter-rater reliability of the components of the asbestos exposure algorithm. The present report is based upon a series of statistical analyses of available

asbestos algorithm data collected in different parts of the country. Empirical distributions and correlations are presented along with available data pertinent to the algorithm's measurement reliability and validity.

Section II below describes the data available for statistical analysis, while Section III summarizes the data collection methods. Section IV presents algorithm variable, algorithm score, and air level distributions. Section V presents intercorrelations between algorithm variables. Section VI presents correlations between the algorithm score and its components, and Section VII presents relationships between the algorithm variables and various dependent variables. Conclusions are presented in Section VIII.

II. DATA AVAILABLE FOR STATISTICAL ANALYSIS

Asbestos exposure assessment algorithm data (hereafter referred to as algorithm data) were available from six different sources. "Asbestos-in-schools Control Programs" located in Montgomery County, Ohio (USEPA 1980a), New York City, and the State of North Carolina willingly supplied their algorithm data sheets (see next section). In addition, three other sources supplied algorithm data and air sampling data. These sources included an EPA study contracted to Battelle (Patton et al. 1980), documentation prepared by Industrial Hygienics (Schirripa 1980, n.d.), and French data obtained by EPA (Stroup 1980). The French data provided by EPA were collected in Paris, France, with the cooperation of Sebastien et al. (1979) at the Laboratories d'Etude des Particules Inhalées, Direction des Affaires Sanitaires et Sociales de Paris.

The data available from Ohio are based upon a survey of all 195 public schools within the jurisdiction of the Montgomery County (Dayton, Ohio) Combined General Health District. All rooms and corridors in these 195 public schools were visually inspected, and bulk samples of suspicious materials on walls or ceilings were collected for laboratory analysis. Overall, one bulk sample was taken for approximately every 5,000 square feet of material having the same color and texture, but additional samples were taken from suspect areas of less than 5,000 square feet. Each time a bulk sample was taken, the physical characteristics of the bulk sampling site were described by circling a numbered response on a survey form. The Montgomery

county survey identified 23 schools with friable asbestos-containing materials in student or teacher areas.

The data available from New York are based upon a survey of all 1,411 buildings or structures operated by the New York City Board of Education. Each space or room in these buildings was visually inspected, and bulk samples of suspicious materials were collected by Division of School Buildings (DSB) personnel. DSB did not follow a uniform sampling rule based upon square footage when bulk samples of suspect material were taken. Rather, DSB's overall approach to the sampling problem was to take one bulk sample from each type of similarly appearing material within each school building. After DSB became aware of the heterogeneity of some of the suspect materials, more than one sample was taken. DSB also described the physical characteristics of the spaces where bulk samples were collected by using a standardized form similar to the one used in Ohio. The DSB survey identified 257 school buildings with friable asbestos-containing materials on ceilings or walls.

The data available from North Carolina are based upon isolated reports from local school administrators to the North Carolina Department of Public Instruction. Thus, the available North Carolina data clearly cannot be extropolated to all schools with friable asbestos-containing material in the state. However, the North Carolina data are based upon the laboratory analysis of bulk samples, and a standardized description of sampling site characteristics similar to the ones noted above.

The data available from Battelle Columbus Laboratories are based upon an EPA sponsored study to evaluate several methods of estimating asbestos exposures in schools. The Battelle data were collected at 64 purposely chosen sites in 22 school buildings. The 64 sites were selected to conform with a modified factorial experimental design based upon material friability and condition. At each of these sites bulk samples were obtained along with ratings of pertinent site characteristics and fiber releasability data.

The data available from Industrial Hygienics are based upon measurements taken in general occupancy buildings and in more specialized structures located in several northeastern states. In each instance, a concern about indoor airborne asbestos levels motivated a request to Industrial Hygienics to evaluate the degree of exposure for a fee. Industrial Hygienics followed a specified data collection protocol when building or structure characteristics were rated and air samples were taken, but the selection of buildings and

structures for study was not guided by an a priori research design. The 40 buildings or structures inspected by Industrial Hygienics included schools, offices, churches, manufacturing facilities, hospitals, ships at sea, ships in port, and a retail store. The buildings were located in urban, suburban, and rural areas.

The data available from Paris, France, are also based upon measurements taken in general occupancy buildings and more specialized structures. The collection of data in a particular building or structure was motivated by a request to the Laboratories d'Etude des Particules Inhalées, although uniform data collection protocols guided the acquisition of building characteristics and airborne asbestos data. The buildings or structures inspected included schools, offices, shopping centers, parking garages, a laboratory, a theater, a post office, a workshop, and a swimming pool.

It should be noted at the outset that only limited conclusions can be drawn from the available data because data collection protocols, adherence to protocols, and the selection of buildings or sites within buildings were not uniform across data sources. Thus, the statistics presented in this report should be viewed as descriptive summaries of the six available data files. These statistics should not be viewed as unbiased estimators of various population parameters because measurement bias and selection bias were not controlled by adherence to an overall study design.

III. DATA COLLECTION METHODS

The data analyzed in this report were obtained by: (1) selecting bulk samples of suspect materials, (2) sampling the air, and (3) rating the physical characteristics of the rooms or areas where the bulk or air samples were collected. The general procedure for collecting the bulk samples is described in the EPA guidance document (USEPA 1979). Polarized light microscopy (PLM) with dispersion staining (McCrone, McCrone, and Delly 1978) was used to estimate the percentage of asbestos in each sample.

Formally, the algorithm data consist of bulk-sampling-based estimates of the percentage of asbestos present in the suspect material and ratings of physical characteristics of areas where the bulk samples were collected. These algorithm data should be kept conceptually distinct from the air-sampling data because the central problem at issue is the empirical relationship between the algorithm data and appropriate air-sampling data.

The ratings of physical characteristics of areas, where the bulk and air samples were collected, were performed by individuals who were very familiar with the physical chracteristic definitions described in the EPA guidance document and with the coding rules described in the EPA algorithm draft report (USEPA 1979b). In fact most of the individual raters were introduced to the algorithm in a formal training session. The EPA convened special asbestos-in-schools training sessions in Ohio, North Carolina, and New York. Supervisory personnel attended these training sessions before organizing school surveys in their respective areas. Battelle Columbus Laboratories (Patton et al. 1980) compared the rating consistency of novice raters and raters who had completed a four-hour training session, and explored the impact of different rating forms upon rating consistency. The data obtained by Battelle from five types of raters with several levels of training were combined and analyzed in this report. The Industrial Hygienics documentation (Schirripa n.d.) does not specifically describe the nature of the training received by the raters who collected their data. Yet the documentation suggests that Industrial Hygienics raters had been collecting the same data for a number of years. The French algorithm data was collected by experienced EPA personnel who also had been using the algorithm for several years.

The EPA procedure requires raters to estimate

(1) the asbestos-containing material's general condition,

(2) the extent of water damage,

(3) the percentage of material exposed,

(4) the degree of accessibility,

(5) the level of human activity present,

(6) the impact of air plenums, and

(7) the material's friability.

The ratings of these seven site characteristics are combined with information from a laboratory analysis of a bulk sample of the friable material to yield an algorithm score. The scoring procedure is described in detail in Appendix A.

A comparison of the algorithm variable codes presented in Appendix A, which is based upon the EPA draft report (USEPA 1979b), and the codes displayed in Tables 1, 4, and 5 below reveals several inconsistencies. The coding inconsistencies involve accessibility, activity, friability, and percent asbestos ratings. The addition of extra codes, or the use of

different coding rules by raters in different data collection sites, suggests that it would be inappropriate to combine the various datasets into a single "master" file for analysis purposes. Nevertheless, since the ratings are only ordinal measurements, gross distortions may not have been introduced by the use of slightly different coding rules by the various raters.

Three different types of air sampling/laboratory protocols were followed. One protocol was developed by the National Institute of Occupational Safety and Health for use in estimating occupational asbestos exposures. This protocol relies upon phase contrast microscopy to count fibers assumed to be asbestos (NIOSH 1977). The second protocol combined phase contrast microscopy with a ceiling vibrator which was used to stimulate the release of asbestos fibers (Patton et al. 1980). The third protocol relies upon transmission electron microscopy (TEM). This protocol is described in a recent report by Sebastien et al. (1979). TEM is an optimal procedure in the sense that asbestos fibers can be distinguished from nonasbestos fibers in the sample, but TEM is expensive and standard measurement protocols have been developed only recently.

The airborne asbestos level data provided by Industrial Hygienics are based upon phase contrast microscopy, while Battelle Laboratories combined this technique with a ceiling vibrator. The airborne asbestos level data from Paris, France are based upon transmission electron microscopy. The availability of the TEM data from France was one motivation for including the Paris data in this report.

IV. VARIABLE DISTRIBUTIONS

A. Basic Features of the Algorithm Data

Table 1 presents frequency distributions of algorithm variables in North Carolina; Montgomery County, Ohio; and the five boroughs of New York City. Inspection of Table 1 reveals the clustering of New York observations in a relatively small number of schools. Specifically, 75 percent of the Manhattan observations were taken in 19 percent (10/54) of the surveyed schools. Similar clustering in the four remaining New York datasets is apparent. The reasons for this clustering cannot be definitively stated because the New York City Asbestos-in-Schools Program did not adhere to a uniform sampling rule when the data were collected. However, the best

Table 1. DISTRIBUTION OF SCHOOL ASBESTOS ALGORITHM VARIABLES

Variable	LOCATIONS WHERE THE DATA WERE COLLECTED						
	North Carolina (Statewide Data)	Montgomery County (Ohio)	Manhattan (New York)	Staten Island (New York)	Bronx (New York)	Brooklyn (New York)	Queens (New York)
Number of Schools	40	23	54	12	67	51	82
Number of Observations	143	76	625	289	613	397	1,289
Number of Schools With 75% of Observations	21	15	10	2	9	13	17
Material Condition Codes	N (%)	N (%)	N (%)	N (%)	N (%)	N (%)	N (%)
0	70 (49)	38 (51)	452 (72)	221 (78)	485 (79)	209 (53)	591 (46)
2	44 (31)	30 (40)	158 (25)	46 (16)	109 (18)	151 (38)	680 (52)
5	29 (20)	7 (9)	12 (2)	15 (5)	16 (3)	37 (9)	24 (2)
	143 (100)	75 (100)	623 (99)[a]	282 (100)	610 (100)	397 (100)	1,275 (100)
Water Damage Codes							
0	121 (85)	41 (55)	522 (84)	232 (82)	551 (90)	288 (73)	1,160 (91)
1	20 (14)	21 (28)	62 (10)	2 (1)	40 (7)	40 (10)	84 (7)
2	2 (1)	5 (7)	41 (6)	48 (17)	22 (3)	69 (17)	31 (2)
	143 (100)	67 (89)[b]	625 (100)	282 (100)	613 (100)	397 (100)	1,275 (100)
Exposed Surface Codes							
0	2 (1)	0 (0)	108 (17)	209 (72)	195 (32)	97 (24)	404 (32)
1	1 (1)	0 (0)	31 (5)	22 (8)	111 (18)	37 (9)	18 (1)
4	140 (98)	75 (100)	486 (78)	58 (20)	307 (50)	263 (66)	853 (67)
	143 (100)	75 (100)	625 (100)	289 (100)	613 (100)	397 (100)	1,275 (100)
Accessibility Codes							
0	33 (23)	--------	256 (41)	213 (74)	360 (59)	145 (37)	394 (31)
1	90 (63)	64 (85)	329 (53)	68 (24)	208 (34)	190 (48)	704 (55)
3	--------	11 (15)	40 (6)	8 (3)	45 (7)	62 (16)	174 (14)
4	20 (14)	--------	--------	--------	--------	--------	--------
	143 (100)	75 (100)	625 (100)	289 (100)	613 (100)	397 (100)	1,272 (100)
Activity Codes							
0	93 (65)	7 (9)	258 (41)	--------	398 (65)	92 (23)	394 (31)
1	45 (31)	24 (32)	330 (53)	251 (87)	172 (28)	212 (53)	704 (55)
2	5 (3)	44 (59)	--------	--------	--------	--------	--------
3	--------	--------	37 (6)	38 (13)	41 (7)	93 (23)	174 (14)
	143 (100)	75 (100)	625 (100)	289 (100)	611 (100)	397 (100)	1,272 (100)
Air Plenum Codes							
0	118 (83)	67 (89)[c]	538 (92)	276 (96)	322 (53)	269 (68)	1,069 (90)
1	25 (17)	8 (11)[d]	48 (8)	13 (4)	291 (47)	127 (32)	120 (10)
	143 (100)	75 (100)	586 (100)	289 (100)	613 (100)	396 (100)	1,189 (100)
Friability Codes							
1	64 (45)	29 (39)	328 (53)	13 (5)	144 (24)	152 (38)	782 (44)
2	50 (35)	43 (57)	141 (23)	2 (1)	430 (70)	56 (14)	19 (2)
3	27 (19)	3 (4)	153 (25)	274 (94)	35 (6)	145 (37)[e]	346 (29)
	141 (99)[f]	75 (100)	622 (100)	289 (100)	609 (100)	353 (89)[g]	1,127 (95)[h]
Asbestos Codes							
0	13 (9)	1 (1)	73 (17)	3 (1)	59 (14)	136 (34)	346 (43)
1	39 (28)	--------	89 (21)	6 (2)	28 (6)	61 (15)	33 (4)
2	58 (41)	64 (85)	111 (26)	179 (62)	348 (80)	156 (39)	83 (10)
3	31 (22)	10 (13)	153 (36)	101 (35)	--------	44 (11)	350 (43)
	141 (100)	75 (100)	426 (100)	289 (100)	435 (100)	397 (100)	812 (100)

[a] 1 observations were coded "1".

[b] 8 observations were coded "3".

[c] 2 observations were coded "0".

[d] 44 observations were coded "0".

[e] 98 observations were coded "0".

[f] A code of "2" instead of "3" was originally used to indicate the presence of an air plenum.

available information suggests that more bulk samples were taken in schools with greater amounts of suspect material, and when there was more concern about the heterogeneity of the suspect material. Table 1 also reveals that the variable water damage has essentially no variation in the Bronx and the Queens datasets; the variable exposed surface has no variation in the North Carolina and Montgomery County datasets; and the variable air plenum has essentially no variation in the Manhattan, Staten Island, and Queens datasets. Examination of the accessibility and the activity code distributions suggests that different coding rules for these variables were used in North Carolina, Montgomery County, and New York City.

Table 1 includes all available observations, but in Table 2 observations were deleted either because (1) missing values on some algorithm variables prevented the calculation of exposure scores; (2) percent asbestos was coded "0"; (3) or random samples of essentially identical observations within the New York schools were taken. Overall, observations were deleted from the original data files (see Table 1) so that the resulting data files (see Table 2) would be more relevant to the focus of this report--namely, the algorithm's measurement reliability and validity. In particular, incomplete observations were deleted so that comparisons between different analyses would not be complicated by varying sample sizes. Observations associated with bulk samples yielding less than 1 percent asbestos (coded "0") were deleted because the scoring system treats these observations as if there were no asbestos present.

In addition, 20 percent of the available observations clustered in the larger New York schools were selected at random from the New York data files to make the New york exposure scores less "skewed" or dominated by the data collected in a few large homogeneous schools with relatively low scores. The dominations of exposure score distributions by observations taken from a few large homogeneous schools with low scores is undesirable because the algorithm was designed to identify situations where exposures are high relative to background levels. Moreover, the homogeneity of the observations from these schools suggests that many observations had been made where one or two would have sufficed. The subsampling procedure applied to the New York City data

Table 2. DISTRIBUTIONS OF SCHOOL ASBESTOS ALGORITHM VARIABLES: CERTAIN OBSERVATIONS DELETED[a]

Variable	North Carolina (Statewide Data)	Montgomery County (Ohio)	Manhattan (New York)	Staten Island (New York)	Bronx (New York)	Brooklyn (New York)	Queens (New York)
	LOCATIONS WHERE THE DATA WERE COLLECTED						
Number of Schools	40	23	54	12	67	51	82
Number of Observations Retained	128	74	110	77	130	155	149
Number of Observations Deleted	15[b]	2[c]	515[d]	212[e]	483[f]	242[g]	1140[h]
	N (%)	N (%)	N (%)	N (%)	N (%)	N (%)	N (%)
Material Condition Codes							
0	63 (49)	37 (50)	78 (71)	51 (66)	89 (68)	67 (68)	84 (56)
2	40 (31)	30 (41)	27 (25)	13 (17)	32 (25)	70 (45)	62 (42)
5	25 (20)	7 (9)	4 (4)	13 (17)	9 (7)	18 (12)	3 (2)
	128 (100)	74 (100)	109 (99)[i]	77 (100)	130 (100)	155 (100)	149 (100)
Water Damage Codes							
0	108 (84)	40 (54)	96 (87)	59 (77)	118 (91)	117 (75)	134 (90)
1	18 (14)	21 (28)[k]	9 (8)	2 (3)	7 (5)	15 (10)	11 (7)
2	2 (2)	5 (7)[k]	5 (5)	16 (21)	5 (4)	23 (15)	4 (3)
	128 (100)	68 (89)	110 (100)	77 (100)	130 (100)	155 (100)	149 (100)
Exposed Surface Codes							
0	2 (2)	----------	22 (20)	45 (58)	39 (30)	24 (15)	58 (39)
1	1 (1)	----------	5 (5)	1 (1)	20 (15)	22 (14)	10 (7)
4	125 (98)	74 (100)	83 (75)	31 (40)	71 (55)	109 (70)	81 (54)
	128 (100)	74 (100)	110 (100)	77 (100)	130 (100)	155 (100)	149 (100)
Accessibility Codes							
0	31 (24)	----------	24 (22)	47 (61)	60 (46)	28 (18)	71 (48)
1	81 (63)	63 (85)	78 (71)	23 (30)	50 (38)	91 (59)	65 (44)
3	----------	11 (15)	8 (7)	7 (9)	20 (15)	36 (23)	13 (9)
4	16 (13)	----------	----------	----------	----------	----------	----------
	128 (100)	74 (100)	110 (100)	77 (100)	130 (100)	155 (100)	149 (100)

Table 2 (continued)

Variable	North Carolina (Statewide Data)	Montgomery County (Ohio)	Manhattan (New York)	Staten Island (New York)	Bronx (New York)	Brooklyn (New York)	Queens (New York)
	LOCATIONS WHERE THE DATA WERE COLLECTED						
Activity Codes							
0	83 (65)	7 (9)	29 (26)	----------	69 (53)	18 (12)	71 (48)
1	40 (31)	24 (32)	73 (66)	55 (71)	44 (34)	70 (45)	38 (26)
2	5 (4)	43 (58)	----------	----------	----------	----------	----------
3	----------	----------	8 7	22 29	17 (13)	67 (43)	40 27
	128 (100)	74 (100)	110 (100)	77 (100)	130 (100)	155 (100)	149 (100)
Air Plenum Codes							
0	105 (82)	66 (89)[l]	95 (86)	71 (92)	65 (50)	92 (59)	119 (80)
1	23 (18)	8 (11)	15 (14)	6 (8)	65 (50)	63 (41)	29 (19)
	128 (100)	74 (100)	110 (100)	77 (100)	130 (100)	155 (100)	148 (99)
Friability Codes							
1	53 (41)	29 (39)	74 (67)	10 (13)	37 (28)	66 (43)	49 (33)
2	48 (38)	42 (57)	4 (4)	2 (3)	75 (58)	27 (17)	8 (5)
3	27 (21)	3 (4)	32 (29)	65 (84)	18 (14)	62 (40)	92 (62)
	128 (100)	74 (100)	110 (100)	77 (100)	130 (100)	155 (100)	149 (100)
Percent Asbestos Codes							
1	39 (30)	----------	33 (30)	6 (8)	28 (22)	61 (39)	18 (12)
2	58 (45)	64 (86)	38 (35)	50 (65)	102 (78)	75 (48)	50 (34)
3	31 (24)	10 (14)	39 (35)	21 (27)	----------	19 (12)	81 (54)
	128 (100)	74 (100)	110 (100)	77 (100)	130 (100)	155 (100)	149 (100)

[a]Observations were deleted because (1) missing values on some algorithm variables prevented the calculation of exposure scores; (2) random samples of essentially identical observations within certain schools were taken; and (3) percent asbestos was coded "0".

[b]2 observations were deleted by missing values, 13 observations were deleted by "0" percent asbestos codes.

[c]1 observation was deleted by mising values, 1 observation was deleted by "0" percent asbestos codes.

[d]207 observations were deleted by missing values, 237 observations were deleted by the sampling operation, 71 observations were deleted by "0" percent asbestos codes.

[e]7 observations were deleted by missing values, 202 observations were deleted by the sampling operation, 3 observations were deleted by "0" percent asbestos codes.

[f]182 observations were deleted by missing values, 245 observations were deleted by the sampling operation, 56 observations were deleted by "0" percent asbestos codes.

[g]No observations were deleted by missing values, 106 observations were deleted by the sampling operation, 136 observations were deleted by "0" percent asbestos codes.

[h]526 observations were deleted by missing values, 297 observations were deleted by the sampling operation, 317 observations were deleted by "0" percent asbestos codes.

[i]1 observation was coded "1".

[j]1 observation was coded "3".

[k]8 observations were coded "3".

[l]A code of "2" instead of "1" was originally used to indicate the presence of an air plenum.

can also be viewed as an adjustment to make the data more representative of the borough school systems, since the clustering of samples in schools varied so widely.

Table 3 displays a subset of the data presented in Table 2; specifically, in Table 3 acoustical tile observations are deleted from the New York files. A rationale for this deletion is that relatively hard acoustical tiles do not contribute to asbestos air concentrations, although there are no data presently available which could be used to test this assumption. A comparison of the friability codes in Tables 2 and 3 suggests that deleting acoustical tile observations changes the friability and the percent asbestos distributions in the five New York City boroughs. When acoustical tile observations are included in the Manhattan data, 29 percent of the total observations received a friability code of "3" (Table 2). When acoustical tile observations are deleted from the Manhattan data, 86 percent of the total observations received a friability code of "3" (Table 3). Similar trends are apparent in the remaining four boroughs. The frequency of the percent asbestos code "1" in each of the five datasets decreases when acoustical tile observations are deleted. It should also be pointed out that deleting acoustical tile observations reduces the statistical variation in friability and percent asbestos thus decreasing the likelihood that friability or percent asbestos will correlate with other variables.

Tables 4 and 5 describe algorithm variable distributions in data sets compiled by Industrial Hygienics (Table 4), Battelle Columbus Laboratories, and the EPA (Table 5). The Industrial Hygienics data (Schirripa 1980, n.d.) were collected from ships at sea and in port, as well as from buildings located in the Northeast. The buildings surveyed included schools, offices, churches, manufacturing facilities, hospitals, and a retail establishment. The Battelle data were collected entirely from school buildings (Patton et al. 1980), but the EPA Paris data were collected in a variety of buildings (Sebastien 1979) like the Industrial Hygienics data.

B. Comparisons Between Algorithm Variable Distributions in Different Locations

Inspection of Tables 2, 4, and 5 suggests that the eight algorithm variables can be ordered in terms of the consistency of frequency distributions across the 10 datasets. If the same algorithm variable code is more frequently selected (by raters) across several datasets, then the datasets

Table 3. DISTRIBUTIONS OF SCHOOL ASBESTOS ALGORITHM VARIABLES: ACOUSTICAL TILE OBSERVATIONS DELETED

Variable	New York Data Sources				
	Manhattan	Staten Island	Bronx	Brooklyn	Queens
Number of Observations	35[a]	65[b]	77[c]	81[d]	96[e]
	N (%)	N (%)	N (%)	N (%)	N (%)
Material Condition Codes					
0	25 (71)	45 (69)	62 (81)	32 (40)	76 (79)
2	8 (23)	8 (12)	13 (17)	40 (49)	18 (19)
5	2 (6)	12 (18)	2 (3)	9 (11)	2 (2)
	35 (100)	65 (100)	77 (100)	81 (100)	96 (100)
Water Damage Codes					
0	32 (91)	48 (74)	72 (94)	72 (89)	86 (90)
1	3 (9)	1 (2)	4 (5)	4 (5)	9 (9)
2	--------	16 (25)	1 (1)	5 (6)	1 (1)
	35 (100)	65 (100)	77 (100)	81 (100)	96 (100)
Exposed Surface Codes					
0	22 (63)	45 (69)	39 (51)	23 (28)	58 (60)
1	5 (14)	1 (2)	20 (26)	18 (22)	10 (10)
4	8 (23)	19 (29)	18 (23)	40 (49)	28 (29)
	35 (100)	65 (100)	77 (100)	81 (100)	96 (100)
Accessibility Codes					
0	22 (63)	46 (71)	41 (53)	26 (32)	66 (69)
1	11 (31)	14 (22)	32 (42)	40 (49)	29 (30)
3	2 (6)	5 (8)	4 (5)	15 (19)	1 (1)
	35 (100)	65 (100)	77 (100)	81 (100)	96 (100)
Activity Codes					
0	23 (66)	--------	58 (75)	10 (12)	55 (57)
1	10 (29)	52 (80)	10 (13)	41 (51)	15 (16)
2	--------	--------	--------	--------	--------
3	2 (6)	13 (20)	9 (12)	30 (37)	26 (27)
	35 (100)	65 (100)	77 (100)	81 (100)	96 (100)
Air Plenum Codes					
0	32 (91)	63 (97)	27 (35)	52 (64)	77 (80)
1	3 (9)	2 (3)	50 (65)	29 (36)	19 (20)
	35 (100)	65 (100)	77 (100)	81 (100)	96 (100)
Friability Codes					
1	5 (14)	-------	-------	-------	-------
2	-------	-------	59 (77)	19 (23)	7 (7)
3	30 (86)	65 (100)	18 (23)	62 (77)	89 (93)
	35 (100)	65 (100)	77 (100)	81 (100)	96 (100)
Percent Asbestos Codes					
1	7 (20)	-------	-------	-------	-------
2	1 (3)	44 (68)	77 (100)	62 (77)	16 (17)
3	27 (77)	21 (32)	-------	19 (23)	80 (83)
	35 (100)	65 (100)	77 (100)	81 (100)	96 (100)

[a] 75 acoustical tile observations were deleted.

[b] 12 acoustical tile observations were deleted.

[c] 33 acoustical tile observations were deleted.

[d] 74 acoustical tile observations were deleted.

[e] 42 acoustical tile observations were deleted, 11 additional observations had missing values for material type.

Table 4. ALGORITHM DATA COLLECTED BY INDUSTRIAL HYGIENICS, INC. IN NORTHEASTERN PUBLIC BUILDINGS

Algorithm	Variables	
	N	(%)
Material Condition Codes		
0	29	(73)
2	5	(13)
5	6	(15)
TOTALS	40	(100)
Water Damage Codes		
0	34	(85)
1	5	(13)
2	1	(2)
TOTALS	40	(100)
Exposed Surface Codes		
0	7	(18)
1	7	(18)
4	26	(65)
TOTALS	40	(100)
Accessibility Codes		
0	3	(7)
1	21	(53)
3	16	(40)
TOTALS	40	(100)
Activity Codes		
0	4	(10)
1	14	(35)
2	2	(5)
3	20	(50)
TOTALS	40	(100)
Air Plenum Codes		
0	32	(80)
1	8	(20)
TOTALS	40	(100)
Friability Codes		
0	12	(30)
1	5	(12)
2	22	(55)
3	1	(3)
TOTALS	40	(100)
% Asbestos Codes		
0	4	(10)
1	7	(17)
2	25	(63)
3	4	(10)
TOTALS	40	(100)

Table 5. DISTRIBUTIONS OF SCHOOL ASBESTOS ALGORITHM VARIABLES

Variable	DATA SOURCES: Battelle (Ohio)		DATA SOURCES: Paris (France)	
Number of Observations	40[a]		23[d]	
Material Condition Codes	N	(%)	N	(%)
0	8	(20)	7	(30)
2	14	(35)	11	(48)
5	18	(45)	5	(22)
	40	(100)	23	(100)
Water Damage Codes				
0	28	(70)	22	(96)
1	5	(13)	1	(4)
2	7	(18)	-	-
	40	(100)	23	(100)
Exposed Surface Codes				
0	-	-	-	-
1	1	(3)	4	(17)
4	39	(98)	19	(83)
	40	(100)	23	(100)
Accessibility Codes				
0	-	-	1	(4)
1	35	(88)	6	(26)
3	5	(13)	-	-
4	-	-	16	(70)
	40	(100)	23	(100)
Activity Codes				
0	9	(23)	3	(13)
1	17	(43)	8	(35)
2	14	(35)	12	(52)
3	-	-	-	-
	40	(100)	23	(100)
Air Plenum Codes				
0	33	(83)	19	(83)
1	7	(18)	4	(17)
	40	(100)	23	(100)
Friability Codes				
1	13	(33)	1	(4)
2	16	(40)	-	-
3	8	(20)	22	(96)
	37	(92)[b]	23	(100)
Percent Asbestos Codes				
0	-	-	14	(61)
1	-	-	-	-
2	31	(78)	9	(39)
3	8	(20)	-	-
	39	(97)[c]	23	(100)

[a] SOURCE: Asbestos In Schools, March 31, 1980. Battelle Columbus Laboratories. Supplementary Table F-1. 29 Observations with different vibrator air measurements were selected randomly, 11 observations had a selection probability of 1.0.

[b] 3 Observations were coded "0".

[c] 1 Observation was coded "0".

[d] 2 Observations had missing values, one observation was deleted because it was considered to be an outlier. Data provided by EPA.

will be termed "consistent" with one another. Thus, datasets can be consistent when one algorithm variable is examined and inconsistent when another variable is examined. The consistency or agreement between datasets is a function of the types of asbestos-containing materials used in different buildings, the sampling procedures which guided data collection, and the inherent reliability of the rating system. However, consistency between datasets with respect to a particular variable does not imply that the corresponding ratings are valid. On the contrary, the ratings may be consistently invalid or biased with respect to the "true" ratings in each location. "Consistent" ratings may also be insensitive to different physical conditions. The most consistent variable is the water damage variable (10/10). In all datasets, the water damage code "0" is most frequently selected. The least consistent variable is the activity variable (3/10). The remaining variables ordered from high to low agreement across datasets are exposed surface (9/10), air plenum (9/10), material condition (8/10), percent asbestos (7/10), accessibility (6/10), and friability (4/10). The most frequently used algorithm variable codes across the 10 datasets are indicated in Table 5A and described in the remaining part of this subsection.

A comparison of the percent asbestos codes in Tables 2, 4, and 5 suggests that the "2" code is the most frequent code, with the exception of the Paris, Queens, and Manhattan datasets. It should be noted that 61 percent of the Paris observations received a 0 percent asbestos code (Table 5). These observations were not deleted from Table 5 because only nine observations would have remained. In the Queens dataset 54 percent of the total observations received an asbestos code of "3," while in the Manhattan dataset, 70 percent of the observations are evenly split between codes of "2" and "3" (Table 2).

A comparison of the friability codes in Tables 2, 4, and 5 reveals that friability codes are less uniform across data sets than percent asbestos codes. The "1" friability code is most frequent in the Manhattan data set, while the "2" code is most frequent in the Ohio (Montgomery County and Battelle), the Bronx, and the Industrial Hygienics datasets. The "3" code is most frequent in the Staten Island, Queens, and Paris datasets. In the North Carolina dataset 80 percent of the observations are evenly split between codes "1" and "2", while in the Brooklyn dataset, 80 percent of the observations are evenly split between codes "1" and "3."

Table 5A. Most Frequently Used Algorithm Variable Codes[a]

Dataset	Algorithm Variable[b]							
	COND	WATDAM	EXPSUR	ACC	ACT	PLEN	FRIB	PERABS
NC[c]	0	0	4	1	0	0	1/2	2
MC	0	0	4	1	2	0	2	2
MN	0	0	4	1	1	0	1	2/3
SI	0	0	0	0	1	0	3	2
BX	0	0	4	0	0	0/1	2	2
BK	0	0	4	1	1/3	0	1/3	2
QN	0	0	4	0	0	0	3	3
IH	0	0	4	1	3	0	2	2
BT	5	0	4	1	1	0	2	2
PA	2	0	4	4	2	0	3	0/2
Consistency	8/10	10/10	9/10	6/10	3/10	9/10	4/10	7/10

a Based upon Tables 2, 4, and 5.

b
COND = material condition
WATDAM = water damage
EXPSUR = exposed surface
ACC = accessibility
ACT = activity
PLEN = air plenum
FRIB = friability
PERABS = % asbestos

c
NC = North Carolina
MC = Montgomery County
MN = Manhattan
SI = Staten Island
BX = Bronx
BK = Brooklyn
QN = Queens
IH = Industrial Hygienics
PA = Paris, France

A comparison of the material condition codes in Tables 2, 4, and 5 demonstrates that the "0" code is most frequent in 8 of the 10 datasets. The "5" code is most frequent in the Battelle dataset, while the "2" code is most frequent in the Paris dataset.

The "0" water damage code is most frequent in all 10 datasets (Tables 2, 4 and 5). The "4" exposed surface code is most frequent in all datasets with the exception of the Staten Island dataset. In the Staten Island dataset the "0" exposed surface codes is most frequent.

A comparison of the accessibility codes shows that the "0" code is most frequent in three datasets, the "1" code is most frequent in six datasets, and the "4" code is most frequent in one dataset. The "0" accessibility code is most frequent in the Staten Island, the Bronx, and the Queens datasets. The "1" code is most frequent in the North Carolina, Montgomery County, Manhattan, Brooklyn, Battelle, and the Industrial Hygienics datasets. The "4" code is most frequent in the Paris dataset.

Each of the four activity codes is most frequent in at least one dataset. The "0" activity code is most frequent in the North Carolina, Bronx, and the Queens datasets. The "1" code is most frequent in the Manhatten, Staten Island, and the Battelle datasets. The "2" code is most frequent in the Montgomery County and the Paris datasets. The "3" code is most frequent in the Industrial Hygienics dataset. In the Brooklyn dataset 88 percent of the available observations are about evenly split between the "1" code and the "3" code.

In 9 of the 10 datasets described in Tables 2, 4, and 5 the "0" air plenum code is most frequent. The single exception is the Bronx dataset in which all observations are evenly split between the code "0" and the code "1."

Interpretations of these consistency data must deal with the fact that agreement between datasets is a function of the materials present in buildings of interest, sampling procedures, and the inherent reliability of the rating system. If uniform materials were present and uniform sampling procedures were used, then the consistency data could provide some information about the reliability of the rating systems. However, very little independent information concerning the materials used in these building is available and sampling procedures were not uniform, thus data consistency should not be interpreted as rating reliability. Nevertheless, these analyses illustrate that kinds of comparisons that can be made when adequate data are available.

Table 6. DISTRIBUTIONS OF ASBESTOS ALGORITHM SCORES

Score Interval Midpoint	LOCATIONS WHERE THE DATA WERE COLLECTED						
	North Carolina (Statewide Data)	Montgomery County (Ohio)	Manhattan (New York)	Staten Island (New York)	Bronx (New York)	Brooklyn (New York)	Queens (New York)
	N (%)	N (%)	N (%)	N (%)	N (%)	N (%)	N (%)
0[b]	15 (11)	1 (1)	179 (43)	3 (1)	242 (56)	142 (36)	557 (70)
10[c]	55 (39)	12 (16)	173 (41)	167 (59)	103 (24)	147 (37)	113 (14)
20	18 (13)	17 (23)	19 (5)	43 (15)	52 (12)	26 (7)	36 (5)
30	13 (9)	16 (21)	2 (0)	15 (5)	14 (3)	6 (2)	13 (2)
40	6 (4)	19 (25)	23 (6)	12 (4)	7 (2)	22 (6)	19 (2)
50	7 (5)	6 (8)	13 (3)	3 (1)	4 (1)	11 (3)	18 (2)
60	8 (6)	1 (1)	4 (1)	6 (2)	2 (0)	18 (5)	9 (1)
70	8 (6)	1 (1)	0 (0)	12 (4)	4 (1)	10 (3)	16 (2)
80	2 (1)	1 (1)	2 (0)	7 (2)	2 (0)	5 (1)	3 (0)
90	0 (0)	0 (0)	1 (0)	9 (3)	1 (0)	0 (0)	10 (1)
100	5 (4)	1 (1)	2 (0)	3 (1)	0 (0)	3 (1)	2 (0)
110	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	1 (0)	0 (0)
120	1 (1)	0 (0)	0 (0)	1 (0)	0 (0)	1 (0)	0 (0)
130	2 (1)	0 (0)	0 (0)	0 (0)	0 (0)	2 (1)	1 (0)
140	1 (1)	0 (0)	0 (0)	1 (0)	0 (0)	1 (0)[a]	0 (0)
TOTAL	141 (100)	75 (100)	418 (100)	282 (100)	431 (100)	397 (100)	797 (100)
Collapsed Intervals							
0-24	88 (62)	30 (40)	371 (89)	213 (76)	397 (92)	315 (79)	706 (89)
25-44	26 (18)	41 (55)	38 (9)	30 (11)	25 (6)	39 (10)	50 (6)
>44	27 (19)	4 (5)	9 (2)	39 (14)	9 (2)	43 (11)	41 (5)
TOTAL	141 (100)	75 (100)	418 (100)	282 (100)	431 (100)	397 (100)	797 (100)

[a] 1 observation fell into the "150" interval and 1 observation fell into the "160" interval.

[b] The first interval ranges from -5 to 4.9, although there were no negative score values.

[c] The second interval ranges from 5 to 14.9, the third interval ranges from 15 to 24.9 etc.

C. Algorithm Score Distributions

Table 6 presents distributions of asbestos algorithm scores based upon all available observations in North Carolina, Montgomery County, and the five New York City boroughs. Table 7 displays similar information except that certain observations were deleted from each dataset, either by 0 percent asbestos codes or by the file sampling operation which was described previously (see Table 2 discussion above). A comparison of the corresponding datasets in Tables 6 and 7 shows that the deletions have made the New York distributions less skewed. For example, 70 percent of the predeletion observations in the Queens file had scores less than five while only 28 percent of the postdeletion observations had scores less than this value.

Inspection of Table 7 reveals that 59 percent of the North Carolina observations had scores less than 25, while only 39 percent of the Montgomery County observations had scores less than this "cut point." In the Manhattan, Staten Island, Bronx, Brooklyn, and Queens files 87 percent, 68 percent, 82 percent, 66 percent, and 72 percent, of the respective observations were below the score cut point of 25.

Table 8 summarizes the effect of deleting acoustical tile observations from the datasets presented in Table 7. The acoustical tile observations were deleted because of the possibility that asbestos-containing acoustical tile in general do not contribute to airborne asbestos levels. However, there are no independent data that can support or refute this hypothesis. In the Manhattan, Bronx, and Queens files, deleting the acoustical tile observations makes the score distributions more skewed. In the Staten Island file, deleting the observations has no major effect on the score distribution. In the Brooklyn file, deleting the observations makes the score distribution less skewed.

Tables 9 and 10 display the algorithm score distributions in the Industrial Hygienics (Table 9), the Battelle, and the Paris datasets (Table 10). A comparison between the collapsed Industrial Hygienics score distribution and the collapsed distributions in Table 7 suggests that Industrial Hygienics file is most similar to the Bronx file. Similar comparisons between Tables 10 and 7 suggest that the Battelle file is most similar to the Montgomery County file, and that the Paris file is most similar to the Staten Island file.

If the 10 datasets described in Tables 7, 9, and 10 are considered simultaneously and a score cut point of 25 is assumed, then it appears that

Table 7. DISTRIBUTIONS OF ASBESTOS ALGORITHM SCORES: CERTAIN OBSERVATIONS DELETED[a]

Score Interval/ Midpoint	LOCATIONS WHERE THE DATA WERE COLLECTED											
	North Carolina (Statewide Data)		Montgomery County (Ohio)		Manhattan (New York)		Staten Island (New York)		Bronx (New York)		Brooklyn (New York)		Queens (New York)	
	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)
0[b]	11	(9)	0	(0)	23	(21)	0	(0)	41	(32)	6	(4)	42	(28)
10[c]	46	(36)	12	(16)	56	(51)	35	(45)	39	(30)	80	(52)	45	(30)
20	18	(14)	17	(23)	17	(15)	17	(22)	26	(20)	17	(11)	20	(13)
30	13	(10)	16	(22)	1	(1)	2	(3)	7	(5)	0	(0)	7	(5)
40	8	(6)	19	(26)	6	(5)	3	(4)	6	(5)	14	(9)	4	(3)
50	5	(4)	6	(8)	5	(5)	2	(3)	2	(2)	4	(3)	10	(7)
60	8	(6)	1	(1)	1	(1)	4	(5)	2	(2)	11	(7)	2	(1)
70	8	(6)	1	(1)	0	(0)	1	(1)	4	(3)	10	(6)	12	(8)
80	2	(2)	1	(1)	1	(1)	4	(5)	2	(2)	3	(2)	2	(1)
90	0	(0)	0	(0)	0	(0)	4	(5)	1	(1)	0	(0)	2	(1)
100	5	(4)	1	(0)	0	(0)	3	(4)	0	(0)	3	(2)	2	(1)
110	0	(0)	0	(0)	0	(0)	0	(0)	0	(0)	1	(1)	0	(0)
120	1	(1)	0	(0)	0	(0)	1	(1)	0	(0)	1	(1)	0	(0)
130	2	(2)	0	(0)	0	(0)	0	(0)	0	(0)	2	(1)	1	(1)
140	1	(1)	0	(0)	0	(0)	1	(1)	0	(0)	1	(1)[d]	0	(100)
TOTAL	128	(100)	74	(100)	110	(100)	77	(100)	130	(100)	155	(100)	149	(100)
Collapsed Intervals														
0 - 24	75	(59)	29	(39)	96	(87)	52	(68)	106	(82)	103	(66)	107	(72)
25 - 44	21	(16)	35	(47)	7	(6)	5	(6)	13	(10)	14	(9)	11	(7)
> 44	32	(25)	10	(14)	7	(6)	20	(26)	11	(8)	38	(25)	31	(21)
Total	128	(100)	74	(100)	110	(100)	77	(100)	130	(100)	155	(100)	149	(100)

[a] Deletions are described in the footnotes attached to Table 2.

[b] The first interval ranges from -5 to 4.9, although there were no negative score values.

[c] The second interval ranges from 5 to 14.9, the third ranges from 15 to 24.9, etc.

[d] 1 observation fell into the "150" interval and 1 observation fell into the "160" interval.

Table 8. DISTRIBUTIONS OF ASBESTOS ALGORITHM SCORES: ACOUSTICAL TILE OBSERVATIONS DELETED[a]

Score Interval Midpoint	New York Data Sources				
	Manhattan	Staten Island	Bronx	Brooklyn	Queens
	N (%)	N (%)	N (%)	N (%)	N (%)
0[b]	23 (66)	0 (0)	38 (49)	5 (6)	41 (43)
10	4 (11)	29 (45)	13 (17)	23 (28)	16 (17)
20	0 (0)	12 (18)	9 (12)	4 (5)	3 (3)
30	0 (0)	2 (3)	2 (3)	0 (0)	4 (4)
40	4 (11)	3 (5)	4 (5)	12 (15)	4 (4)
50	3 (9)	2 (3)	2 (3)	3 (4)	10 (10)
60	1 (3)	3 (5)	2 (3)	11 (14)	2 (2)
70	0 (0)	1 (2)	4 (5)	10 (12)	10 (10)
80	0 (0)	4 (6)	2 (3)	3 (4)	2 (2)
90	0 (0)	4 (6)	1 (1)	0 (0)	2 (2)
100	0 (0)	3 (5)	0 (0)	3 (4)	1 (1)
110	0 (0)	0 (0)	0 (0)	1 (1)	0 (0)
120	0 (0)	1 (2)	0 (0)	1 (1)	0 (0)
130	0 (0)	0 (0)	0 (0)	2 (2)	1 (1)
140	0 (0)	1 (2)	0 (0)	3 (4)	0 (0)
TOTAL	35 (100)	65 (100)	77 (100)	81 (100)	96 (100)
Collapsed Intervals					
0 - 24	27 (77)	41 (63)	60 (78)	32 (40)	60 (63)
25 - 44	4 (11)	5 (8)	6 (8)	12 (15)	8 (8)
> 44	4 (11)	19 (29)	11 (14)	37 (46)	28 (29)
TOTAL	35 (100)	65 (100)	77 (100)	81 (100)	96 (100)

[a] Deletions are described in Table 3 footnotes.

[b] First interval ranges from -5 to 4.9, second interval ranges from 5 to 14.9, third interval ranges from 15 to 24.9

Table 9. DISTRIBUTION OF THE ALGORITHM SCORE DATA COLLECTED BY INDUSTRIAL HYGIENICS, INC. IN THE NORTHEAST

Score Interval Midpoint	N	(%)
0	17	(43)
10	6	(15)
20	9	(23)
30	4	(10)
40	2	(5)
50	1	(3)
60	0	(0)
70	1	(3)
80	0	(0)
TOTALS	40	(100)
Collapsed Intervals		
0 - 24	32	(80)
25 - 44	6	(15)
> 44	2	(5)
TOTALS	40	(100)

Table 10. DISTRIBUTIONS OF ASBESTOS ALGORITHM SCORES

Score Interval Midpoint	DATA SOURCES: Battelle (Ohio) N	Battelle (Ohio) (%)	Paris (France) N	Paris (France) (%)
0[a]	3	(8)	14[c]	(61)
10[b]	3	(8)	0	(0)
20	10	(25)	0	(0)
30	7	(18)	0	(0)
40	5	(13)	1	(4)
50	3	(8)	2	(9)
60	1	(3)	2	(9)
70	0	(0)	3	(13)
80	4	(10)	1	(4)
90	0	(0)	0	(0)
100	3	(8)	0	(0)
110	0	(0)	0	(0)
120	0	(0)	0	(0)
130	0	(0)	0	(0)
140	1	(3)	0	(0)
TOTAL	40	(100)	23	(100)
Collapsed Intervals				
0 - 24	16	(40)	14	(61)
25 - 44	12	(30)	1	(4)
>44	12	(30)	8	(35)
Total	40	(100)	23	(100)

[a] The first interval ranges from -5 to 4.9 although there were no negative score values.

[b] The second interval ranges from 5 to 14.9, the third ranges from 15 to 24.9, etc.

[c] At 14 sites <1% chrysotile was detectable in the bulk samples. This laboratory result is coded as "0" percent asbestos.

the New York and the Industrial Hygienics observations have the lowest scores because between 70 and 90 percent of the observations are below the cutpoint. This same cutpoint suggests that the Montgomery County and the Battelle observations have the highest scores because only 39 to 40 percent of the observations in these files are below the cutpoint. The North Carolina and the Paris observations appear to have intermediate scores because 59 to 61 percent of the observations are below the score cutpoint. If a cutpoint of 44 were assumed, then the Paris observations would appear to have the highest scores.

Any conclusions based upon the ten score distributions in Tables 7, 9, and 10 must also deal with the fact that agreement (or disagreement) between datasets is a function of materials present in the buildings of interest, sampling and coding procedures, and the inherent reliability of the rating system. Since independent data about building materials are not available, and uniform sampling and coding procedures were not followed, conclusions based upon these data must be highly provisional.

Table 11 presents the distribution of an alternative algorithm score constructed from information present in the Battelle dataset. This alternative score contains more statistical information than the original (Battelle) score (characterized in Table 10) because the alternative score does not require the categorization of the percent asbestos variable. To form the alternative score, ratings of material condition, water damage, exposed surface, accessibility, activity, and air are first summed. This sum is then multiplied by friability rating and the uncategorized (uncoded) percentage of asbestos present in the bulk sample.

D. Asbestos Air Level Distributions

Tables 12, 13, and 14 display asbestos air level distributions which represent three different measurement approaches. Table 12 is based upon air samples collected by Industrial Hygienics and analyzed by phase contrast microscopy. The data collection protocol followed by Industrial Hygienics was originally developed for use in occupational settings (Schirripa n.d.) where the present asbestos air standard is two fibers per cubic centimeter of air (USOSHA 1972). Table 13 is based upon air samples collected by Battelle Columbus Laboratories and also analyzed by phase contrast microscopy. However, Battelle did not follow the occupational sampling protocol; Battelle used a mechanical vibrator to stimulate the

Table 11. DISTRIBUTION OF SCOR2[a]

Midpoint SCOR2 Interval	N[b]	(%)
0	19	(48)
400	4	(10)
800	6	(15)
1200	3	(8)
1600	1	(3)
2000	5	(13)
2400	0	(0)
2800	1	(3)
3200	0	(0)
3600	1	(3)
TOTAL	40	(100)

[a]SCOR2 = (COND + WATDAM + EXPSUR + ACC + ACT + PLAN)(FRIB)(Uncoded % Asbestos).

[b]SOURCE: Asbestos In Schools, March 3, 1980, Battelle Columbus Laboratories.

Table 12. DISTRIBUTION OF THE ASBESTOS AIR LEVEL DATA COLLECTED BY INDUSTRIAL HYGIENICS, INC. IN THE NORTHEAST

Air Level Interval Midpoint*	N	(%)
0.00	17	(43)
0.05	16	(40)
0.10	3	(8)
0.15	1	(3)
0.20	2	(5)
0.25	0	(0)
0.30	0	(0)
0.35	0	(0)
0.40	0	(0)
0.45	1	(3)
TOTALS	40	(100)

* Fibers/cubic centimeter by phase contrast microscopy.

Table 13. DISTRIBUTION OF STIMULATED FIBER-RELEASABILITY MEASUREMENTS[a]

Midpoint Air Level Interval[b]	N	(%)
0	20	(50)
10	2	(5)
20	1	(3)
30	1	(3)
40	2	(5)
50	0	(0)
60	4	(10)
70	0	(0)
80	0	(0)
90	0	(0)
100	2	(5)
.	.	.
.	.	.
.	.	.
160	2	(5)
.	.	.
.	.	.
.	.	.
240	5	(13)
.	.	.
.	.	.
.	.	.
560	1	(3)
TOTAL	40	(100)

[a]SOURCE: Asbestos In Schools, March 31, 1980. Battelle Columbus Laboratories.

[b]fibers/cm^3, determined by phase contrast microscopy of Millipore filters. A modified scripto vibrator was used to agitate the surface of ceiling materials.

Table 14. DISTRIBUTION OF CHRYSOTILE TEM[a]
AIR LEVEL MEASUREMENTS

Midpoint Air Level Interval[b]	N	(%)
0	11	(48)
5	4	(17)
10	2	(9)
15	0	(0)
20	1	(4)
25	0	(0)
30	0	(0)
35	0	(0)
40	1	(4)
45	0	(0)
50	1	(4)
⋮	⋮	⋮
105	1	(4)
⋮	⋮	⋮
130	1	(4)
⋮	⋮	⋮
145	1	(4)
TOTAL	23	(100)

[a] Transmission electron microscopy, data collected in Paris, France. Analysis was restricted to the chrysotile data because these data were more complete.

[b] nanograms/m^3. First interval ranges from -2.50 to +2.49 although there were no negative values. Second interval ranges from 2.50 to 7.49. Third interval ranges from 7.50 to 12.49, etc.

release of fibers from ceiling materials into sealed chambers from which air samples were taken. Table 14 is based upon air samples collected by Sebastien et al. (1979) and analyzed by transmission electron microscopy. After taking air samples outside of buildings in different areas of Paris, Sebastien et al. suggest that 7 nanograms per cubic meter is a reasonable estimate of ambient Paris asbestos air concentrations in the absence of point sources. Nicholson et al. (1978) summarize similar data collected from 48 United States cities during 1969 and 1970. The data suggest that 94 percent of the air samples examined had concentrations less than 10 nanograms per cubic meter. In an earlier report, Nicholson et al. (1975) describe the air level data collected inside and outside 19 public buildings in the United States. Fifteen percent of the samples collected inside buildings where fibrous asbestos spray was used yielded levels less than 5.1 nanograms per cubic meter, while 25 percent of the samples collected outside these buildings yielded levels less than 5.1 nanograms per cubic meter. A formal statistical comparison (Logue 1980) suggested that the Paris data are not significantly different from Nicholson's data, but this comparison has limited importance because its statistical power is low. If 7 nanograms per cubic meter is considered to be the "cutoff" point, then 65 percent of the observations summarized in Table 14 are within background levels. The Battelle asbestos air level data cannot be compared to the data collected by Nicholson et al. (1975, 1978) because different sampling protocols and analytical techniques were employed.

V. CORRELATIONS BETWEEN ALGORITHM VARIABLES

A. Introduction

Table 15 presents Spearman rank order correlations between the algorithm variables in the North Carolina, Montgomery County, and the New York City files. Within each file the correlations are based upon different numbers of observations because some observations are not complete. Table 15 is based upon the data presented in Table 1.

Table 16 has the same format as Table 15, but the number of observations retained within each of the seven datasets is constant across Spearman correlations. Observations with missing values, with 0 percent asbestos codes, or which cluster in certain large homogeneous New York City Schools have been deleted. Table 16 is based upon the data in Table 2.

Table 15. SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM VARIABLES

Variable	* Variable	LOCATIONS WHERE THE DATA WERE COLLECTED: North Carolina[a] (Statewide Data)	Montgomery County[b] (Ohio)	Manhattan[c] (New York)	Staten Island[d] (New York)	Bronx[e] (New York)	Brooklyn[f] (New York)	Queens[g] (New York)
Material Condition	* Water Damage	.126	.628[h]	.220[h]	-.022	.177[h]	.236[h]	.229[h]
	* Exposed Surface	-.173[h]	.000[h]	.086[h]	.857[h]	.402[h]	.474[h]	.690[h]
	* Accessibility	.482[h]	.241[h]	.320[h]	.840[h]	.509[h]	.676[h]	.469[h]
	* Activity	.162	.136	.228[h]	.431[h]	.496[h]	.197[h]	.167[h]
	* Air Plenum	-.078[h]	.166	.121[h]	.337[h]	-.196[h]	.132[h]	.005[h]
	* Friability	.429[h]	.195	.082[h]	-.226[h]	.034	.005	-.412[h]
	* % Asbestos	.187	-.193	-.216[h]	.159[h]	-.357	-.144	-.664[h]
Water Damage	* Exposed Surface	.062	.000	.133[h]	-.102	.146[h]	.190[h]	.182[h]
	* Accessibility	-.121	.186	.043	-.077	.108[h]	.278[h]	.116[h]
	* Activity	-.080	.163	.062	-.024	.157[h]	.140[h]	.065[h]
	* Air Plenum	-.146	.226[h]	.062[h]	-.057	-.006	.229[h]	.087[h]
	* Friability	-.026	.239[h]	-.120[h]	.033	.057[h]	-.139[h]	-.116[h]
	* % Asbestos	-.163	-.295[h]	-.245[h]	-.032	-.179[h]	-.207[h]	-.154[h]
Exposed Surface	* Accessibility	.066	.000	.427[h]	.945[h]	.346[h]	.587[h]	.712[h]
	* Activity	.106	.000	.394[h]	.480[h]	.488[h]	-.014	.373[h]
	* Air Plenum	.067	.000	.131[h]	.353[h]	-.597[h]	.079	.005[h]
	* Friability	-.099	.000	-.759[h]	-.414[h]	-.404[h]	-.562[h]	-.519[h]
	* % Asbestos	-.153	.000	-.786[h]	.162	-.623[h]	-.627[h]	-.734[h]
Accessibility	* Activity	.147	.204	.723[h]	.468[h]	.470[h]	.341[h]	.344[h]
	* Air Plenum	-.086[h]	-.143[h]	.102[h]	.368[h]	-.021	.241[h]	.037[h]
	* Friability	.175[h]	-.245[h]	-.574[h]	-.361[h]	-.069[h]	-.086[h]	-.497[h]
	* % Asbestos	.058	.070	-.235[h]	.148[h]	-.134[h]	-.232[h]	-.729[h]
Activity	* Air Plenum	-.137[h]	-.253[h]	.129[h]	.261[h]	-.222[h]	.359[h]	.193[h]
	* Friability	.116	-.066	-.448[h]	-.467[h]	-.098[h]	.270[h]	-.080[h]
	* % Asbestos	.122	.077	-.165[h]	-.051	-.441[h]	.247[h]	-.127[h]
Air Plenum	* Friability	-.039	.126	.021[h]	-.324[h]	.350[h]	-.074	.099[h]
	* % Asbestos	-.136	-.117	-.179[h]	.001	.418[h]	-.035	.068
Friability	* % Asbestos	.696[h]	-.121	.570[h]	.340[h]	.288[h]	.858[h]	.848[h]

[a] 141-143 available observations.

[b] 75 available observations.

[c] 418-625 available observations.

[d] 282-289 available observations.

[e] 432-613 available observations.

[f] 397 available observations.

[g] 810-1,275 available observations.

[h] P-value less than 0.05, for the test of hypothesis that the correlation is significantly different from zero.

Table 16. SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM VARIABLES: CERTAIN OBSERVATIONS DELETED[a]

Variable	* Variable	North Carolina (Statewide Data) N = 128	Montgomery County (Ohio) N = 74	Manhattan (New York) N = 110	Staten Island (New York) N = 77	Bronx (New York) N = 130	Brooklyn (New York) N = 155	Queens (New York) N = 149
		LOCATIONS WHERE THE DATA WERE COLLECTED						
Material Conditions	* Water damage	.136[b]	.624[b]	.395[b]	-.209[b]	.173[b]	.102[b]	.278[b]
	* Exposed Surface	-.185[b]	.000	.182	.825[b]	.525[b]	.363[b]	.655[b]
	* Accessibility	.453[b]	.237[b]	.337[b]	.829[b]	.619[b]	.557[b]	.636[b]
	* Activity	.164	.148	.167[b]	.371[b]	.454[b]	.237[b]	.347[b]
	* Air plenum	-.073[b]	.162	.303[b]	.198	-.264[b]	.110	.235[b]
	* Friability	.471[b]	.205[b]	.087	-.091	-.069	.123	-.622[b]
	* % Asbestos	.284[b]	-.243[b]	-.336[b]	.062	-.106	.124	.522[b]
Water Damage	* Exposed Surface	.067	.000	.120[b]	-.299[b]	.141[b]	.196[b]	.104[b]
	* Accessibility	-.123	.184	.215[b]	-.265[b]	.233[b]	.222[b]	.182[b]
	* Activity	-.103	.175	.237[b]	-.156	.168	.167[b]	.161[b]
	* Air plenum	-.146	.223[b]	.172	-.160	-.007	.255[b]	.160
	* Friability	-.019[b]	.249[b]	-.150	.168	-.019	-.289[b]	-.019
	* % Asbestos	-.203[b]	-.348[b]	-.195	-.019	-.093	-.266[b]	.001
Exposed Surface	* Accessibility	.066	.000	.796[b]	.923[b]	.558[b]	.541[b]	.790[b]
	* Activity	.113	.000	.709[b]	.587[b]	.677[b]	.341[b]	.601[b]
	* Air plenum	.073	.000	.176[b]	.351[b]	-.429[b]	.216[b]	.131[b]
	* Friability	-.094	.000	-.850[b]	-.518[b]	-.289[b]	-.322[b]	-.621[b]
	* % Asbestos	-.151	.000	-.673[b]	-.193	-.459[b]	-.355[b]	-.791[b]
Accessibility	*Activity	.132	.210	.593[b]	.592[b]	.414[b]	.252[b]	.499[b]
	* Air plenum	-.084[b]	-.145[b]	.216[b]	.379[b]	-.232[b]	.135[b]	.021[b]
	* Friability	.230[b]	-.242[b]	-.664[b]	-.443[b]	-.125	-.186[b]	-.614[b]
	* % Asbestos	.155	.057	-.560[b]	-.193	-.038	-.218[b]	-.724[b]
Activity	* Air plenum	-.164	-.251[b]	.229[b]	.245[b]	-.265[b]	.278[b]	.222[b]
	* Friability	.137	-.074	-.487[b]	-.459[b]	-.131[b]	-.044	-.118[b]
	* % Asbestos	.157	.115	-.399[b]	-.239[b]	.232[b]	-.104	-.401[b]
Air Plenum	* Friability	-.055[b]	.130	.055[b]	-.402[b]	.160[b]	-.122	.098
	* % Asbestos	-.180[b]	-.138	-.255[b]	.025	.225[b]	-.066	-.059
Friability	* % Asbestos	.690[b]	-.101	.576[b]	.502[b]	.355[b]	808[b]	759[b]

[a] deletions are described in the footnotes attached to Table 2.

[b] P-value less than 0.05, for the test of the hypothesis that the correlation is significantly different from zero.

Inspection of Table 16 reveals that there are positive and negative correlations between score components in each of the seven datasets. The existence of a large positive correlaton accompanied by a small p-value implies that higher ratings of one characteristic are associated with higher ratings of another characteristic in the data file. The existence of a large negative correlation accompanied by a small p-value implies that higher ratings of one characteristic are associated with lower ratings of another characteristic in the data file.

However, the p-values included in Table 16 do not imply that statistical inferences can be legitimately made from the available data to some larger population of eligible sites in North Carolina, Ohio, and New York. On the contrary, the p-values in Table 16 should only be interpreted as convenient indices of the magnitude of the observed correlations relative to the magnitude of the observed variation upon which the correlations are based.

B. Correlations Involving Material Condition

In Table 16 material condition is positively associated with accessibility and activity in each of the seven datasets. Given the nature of the ratings, this consistency supports the proposition that high accessibility and activity both contribute to material damage, but accessibility appears to have a stronger relationship to material damage. Water damage appears to be making a contribution to generalized material deterioration in the Montgomery County and Manhattan data, but to a lesser extent in the Queens data. Table 16 also suggests that exposed surfaces are more likely than unexposed surfaces to be deteriorating in four of the five New York boroughs. Air plenums appear to be associated with material condition in the Manhattan, Bronx, and Queens files, but two of the correlations are positive while the third is negative. It is possible that this inconsistency is a function of building characteristics that were not measured. Friability is positively associated with a deteriorating material condition in the North Carolina, and possibly the Montgomery County, data, but friability is negatively associated with a deteriorating material condition in the Queens' file.

Percent asbestos is positively associated with deteriorating material condition only in the North Carolina and the Queens datasets. In the Montgomery County and the Manhattan files, percent asbestos is negatively associated with deteriorating material conditions. This inconsistency also may be explained by unmeasured building characteristics.

C. Correlations Involving Water Damage

The positive relationship between water damage and material condition in two datasets was noted above. Water damage is unrelated to the amount of exposed surface in five of seven datasets. In the Staten Island file the relationship is negative, while in the Brooklyn file it is positive. In four of the five New York files water damage is positively related to accessibility. The exception is the Staten Island file where the correlation is negative. Activity has a weak positive relationship with water damage in the Manhattan, Brooklyn, and Queens datasets. The presence of an air plenum is weakly associated with water damage in the Brooklyn dataset only. In the Montgomery County file, friability and water damage are positively associated, but in the Brooklyn file, the corresponding correlation is negative. Water damage and percent asbestos are consistently negatively related in three datasets--North Carolina, Montgomery County, and Brooklyn. In the remaining four datasets, there is no relationship between these two variables.

D. Correlations Involving Exposed Surface

Reference has already been made to the generally positive relationship between exposed surfaces and deteriorating material conditions in the New York data and to the fact that exposed surfaces are not correlated with water damage in five of seven datasets. In each of the New York datasets there also is a moderate to strong positive relationship between exposed surfaces and accessibility or activity. In each of the New York files and in the North Carolina data there is a consistently negative relationship between exposed surfaces and friability or percent asbestos. The relationship between exposed surfaces and air plenums is much less consistent. In the Staten Island and the Brooklyn files the correlation is positive, while in the Bronx file the correlation is negative.

E. Correlations Involving Accessibility

Reference has already been made to the generally positive relationships between accessibility and deteriorating material conditions, water damage, or exposed surfaces, particularly in the New York files. Inspection of Table 16 suggests that accessibility is also positively related to activity levels in all seven datasets. Friability is negatively related to accessibility in all files, except for North Carolina, where the relationships is positive. Percent asbestos is negatively related to accessibility in the Manhattan, the Brooklyn, and the Queens datasets. Air plenum is positively related to

accessibility in the Manhattan and the Staten Island datasets, but it is negatively related to accessibility in the Bronx dataset.

F. Correlations Involving Activity

Reference has already been made to the consistently positive relationships between activity and deteriorating material conditions or accessibility. Similar positive relationships between activity and exposed surfaces or water damage in the New York data have been noted. Activity has a positive relationship with air plenums in four of the five New York files, but in the Bronx file and the Montgomery County file the correlation is negative. There are consistently negative correlations between activity and friability in six datasets, but some of the correlations are very small. There are also consistently negative relationships between activity and percent asbestos in the Manhattan, Staten Island, and the Queens datasets. In the Bronx dataset the relationship between activity and percent asbestos is positive.

G. Correlations Involving Air Plenum

Reference has already been made to the generally inconsistent relationship between air plenums and material condition, water damage, exposed surfaces, or accessibility in Table 16. But, as mentioned above, air plenums are positively related to activity in four of five New York datasets. In six of the seven datasets friability has no relationship with air plenums. The exception is the Staten Island dataset where the correlation is negative. Percent asbestos is negatively related to air plenums in the North Carolina and the Manhattan files, but the corresponding correlation is positive in the Bronx dataset.

H. Correlations Involving Friability

The impressively consistent relationships between friability and exposed surfaces, accessibility or activity were mentioned above. For each of these variables the correlations with friability were negative in six of seven datasets. The correlations between friability and material condition, water damage, and air plenum are much less consistent. Coded percent asbestos has a positive relationship with friability in six of the seven datasets in Table 16. The exception is Montgomery County where there is no relationship between these two variables.

I. Correlations Involving Percent Asbestos

It was noted above that coded percent asbestos was negatively related to exposed surfaces in six of seven datasets. Yet it was also just

noted that percent asbestos has a positive relationship with friability in six of seven datasets. Water damage, accessibility, and activity are negatively associated with percent asbestos in three datasets each. Air plenum is negatively associated with percent asbestos in two datasets and positively associated in a third, while material condition is positively associated with percent asbestos in two datasets and negatively associated in two others.

J. School's Program Summary

Table 16A summarizes the more important information presented in Table 16 and discussed above. Specific associations are included in Table 16A if there is evidence supporting the associations in several (Table 16) datasets. Inspection of Table 16A reveals that no algorithm variables are highly correlated in the majority of the seven datasets. The percent asbestos/friability correlation is moderately positive, but the remaining percent asbestos correlations are generally small. Among the remaining friability correlations, the moderately negative friability/accessibility correlation should be noted. Finally, material condition has moderately positive correlations with accessibility and exposed surfaces, while exposed surfaces has moderately positive correlations with accessibility and activity. All other correlations appear to be consistently small when all seven datasets are considered.

K. Observational Deletion Effects Upon Intercorrelations

The magnitude, algebraic sign, and the p-value associated with each of the Spearman correlations presented in Table 16 may be a function of the specific observations retained in each dataset. A systematic comparison of the information presented in Tables 15 and 16 reveals that the algebraic signs of the vast majority of the correlations presented in Table 16 are identical to the corresponding algebraic signs in Table 15. A similar comparison of relative correlation magnitudes suggests that the pattern of large and small correlations in Table 16 is essentially identical to the pattern in Table 15. Seven exceptions to these generalizations will be described. It is of interest that these seven exceptions all involve the variable "percent asbestos" (coded).

In Table 15 the correlation between percent asbestos and material condition is negative in the Brooklyn and Queens datasets. In Table 16 the corresponding correlations are positive. In addition, a comparison of the Bronx percent asbestos/material condition correlations in Tables 15 and 16

Table 16A. SUMMARY OF ALGORITHM VARIABLE INTERCORRELATIONS[a]

Variable	Variable (Direction)[b]	
	Slightly Correlated	Moderately Correlated
Material Condition	[c]ACT(+),WATDAM(+) FRIB(±),PERABS(±)	ACC(+),EXPSUR(+)
Water Damage	ACC(+)	
Exposed Surface	FRIB(-),PERABS(-)	ACC(+),ACT(+)
Accessibility	PERABS(-)	ACT(+),FRIB(-)
Activity	PLEN(+),FRIB(-) PERABS(±)	
Air Plenum	PERABS(±)	
Friability		PERABS(+)

[a] Based upon Table 16.

[b] (+) positively correlated, (-) negatively correlated, (±) positively and negatively correlated.

[c] Accessibility (ACC), activity (ACT), water damage (WATDAM), exposed surface (EXPSUR), air plenum (PLEN), friability (FRIB), % asbestos (PERABS).

reveals a decrease in this relationship in Table 16. Taken together, the changes in these three correlations suggest that the observations deleted from Table 16 have had an impact on the percent asbestos-material condition correlation in three New York files.

In Table 15, the Queens correlation between percent asbestos and water damage is negative, while the corresponding correlation in Table 16 is very slightly positive. This change is probably caused by deleting the same observations whose absence is responsible for the percent asbestos/material condition correlation changes noted above. This logic is supported by the positive material condition/water damage correlations in Tables 15 and 16.

In Table 15 the Bronx percent asbestos/activity correlation is negative, while the corresponding Table 16 correlation is positive. It is possible that the deletions responsible for this change are identical to those responsible for the decrease in the Bronx percent asbestos/material condition correlation noted above, since the Bronx activity/material condition correlation is moderately positive.

In Table 15 the Staten Island percent asbestos/exposed surface correlation is positive, while the corresponding correlation in Table 16 is negative. A similar change is noted when the Staten Island percent asbestos/accessibility correlations in Tables 15 and 16 are compared. Since the Staten Island exposed surface/accessibility correlation is large and positive, it is reasonable to assume that the deletion of the same observations is responsible for the changes in the percent asbestos/exposed surface and the percent asbestos/accessibility correlation.

L. Acoustical Tile Deletions and Intercorrelations

Table 17 displays a subset of the New York data in Table 16--namely algorithm variable intercorrelations with acoustical tile observations deleted. A comparison of the direction and the magnitude of correlations in the two tables reveals two patterns of changes. Correlations which did not involve friability or percent asbestos generally increased when acoustical tile observations were deleted, while correlations which involved these variables frequently changed sign. The increase in the correlations which do not involve percent asbestos or friability may be attributed to the increased homogeneity of the observations within each New York dataset when acoustical tile observations were deleted. But the increase in homogeneity was accompanied by a decrease in variability. When a decrease in variability is

Table 17. SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM VARIABLES: ACOUSTICAL TILE OBSERVATIONS DELETED[a]

		New York Data Sources				
Variable	* Variable	Manhattan N=35	Staten Island N=65	Bronx N=77	Brooklyn N=81	Queens N=96
Material Condition	*Water Damage	.441[b]	-.241[b]	.134[b]	.330[b]	.421[b]
	*Exposed Surface	.754[b]	.985[b]	.621[b]	.765[b]	.565[b]
	*Accessibility	.730[b]	.936[b]	.527[b]	.799[b]	.639[b]
	*Activity	.880[b]	.492[b]	.739[b]	.504[b]	.478[b]
	*Air Plenum	.569[b]	.251[b]	-.200[b]	.249[b]	.388[b]
	*Friability	-.082[b]	.000	.662[b]	.443[b]	.455[b]
	*% Asbestos	-.437[b]	.134	.000	.057	-.175
Water Damage	*Exposed Surface	.324[b]	-.259[b]	.187[b]	.182[b]	.227[b]
	*Accessibility	.357[b]	-.236	.300[b]	.285[b]	.281[b]
	*Activity	.382[b]	-.120	.100	.038	.192
	*Air Plenum	-.094	-.106	-.032	.062	.169
	*Friability	-.167	.000	.108	.195	-.048
	*% Asbestos	-.083	-.107	.000	.075	.062
Exposed Surface	*Accessibility	.974[b]	.950[b]	.879[b]	.668[b]	.811[b]
	*Activity	.901[b]	.511[b]	.642[b]	.530[b]	.791[b]
	*Air Plenum	.400[b]	.272[b]	-.289[b]	.252[b]	.120
	*Friability	-.635[b]	.000	.698[b]	.418[b]	-.150[b]
	*% Asbestos	-.844[b]	.096	.000	.125	-.632[b]
Accessibility	*Activity	.917[b]	.527[b]	.527[b]	.331[b]	.696[b]
	*Air Plenum	.357[b]	.301[b]	-.236[b]	.119	.111
	*Friability	-.600[b]	.000	.463[b]	.396[b]	-.323[b]
	*% Asbestos	-.738[b]	.044	.000	.060	-.611[b]
Activity	*Air Plenum	.455[b]	.356[b]	-.323[b]	.480[b]	.235[b]
	*Friability	-.350[b]	.000	.839[b]	.269[b]	-.051[b]
	*% Asbestos	-.629[b]	.066	.000	.108	.636[b]
Air Plenum	*Friability	.125	.000	-.430	-.012	.139
	*% Asbestos	-.332	.067	.000	.073	-.199
Friability	*% Asbestos	.775[b]	.000	.000	.306[b]	-.125

[a] Deletions are described in the footnotes attached to Table 3.

[b] P-value less than 0.05, for the test of the hypotheses that the correlation is significantly different from zero.

extreme (variance = zero) the correlation involving this variable will be zero. In Table 3, it is apparent that there is no friability variation in the Staten Island dataset when acoustical tile observations are deleted. Table 3 also reveals that there is no percent asbestos variation in the Bronx dataset when acoustical tile observations are deleted.

A systematic comparison of Tables 16 and 17 highlights those correlations which changed sign and magnitude when acoustical tile observations were deleted. The Bronx correlation between friability and material condition changed from slightly negative to moderately positive. The corresponding Queens correlation changed from moderately negative to moderately positive. The Brooklyn correlation between friability and water damage changed from moderately negative to slightly positive. The Brooklyn and the Bronx correlations between accessibility and friability changed from slightly negative to moderately positive. Similar changes in the Brooklyn and Bronx correlations between activity and friability occurred when acoustical tile observations were deleted. In the Queens dataset the moderately negative correlation between activity and percent asbestos became moderately positive, while the strongly positive correlation between friability and percent asbestos became slightly negative. The occurrence of the above changes in the Bronx, Brooklyn, and Queens files when acoustical tile observations were deleted emphasizes the dependency of algorithm variable intercorrelations upon operational procedures. The exclusion of asbestos-containing acoustical tile data from an exposure survey is scientifically defensible if there are adequate data to support the proposition that these tiles do not contribute to asbestos air levels.

M. Intercorrelations in the Industrial Hygienics, the Battelle, and the Paris Datasets

Table 18 presents algorithm variable intercorrelations estimated from information contained in the Industrial Hygienics, the Battelle, and the Paris datasets. Inspection of Table 18 suggests that water damage, activity, and percent asbestos are the variables most closely associated with deteriorating material conditions. In contrast, inspection of Table 16 suggested that accessibility and exposed surfaces were more closely associated with material condition.

The positive association between water damage and material conditions present in Table 18 was just noted. Other variables correlated with water

Table 18. SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM VARIABLES

Variable	* Variable	Industrial Hygienics (Northeast) N = 40	Battelle (Ohio) N = 40	Paris (France) N = 23	Paris (France) N = 94[a]
		DATA SOURCES			
Material Condition	*Water damage	.705[b]	.307	-.278	.000
	*Exposed Surface	.286	-.165	-.056	.000
	*Accessibility	.245	.276[b]	.227	-.509
	*Activity	.408[b]	.348[b]	.146	-.148
	*Air plenum	-.149	.308	-.094	-.166
	*Friability	-.159	.301	-.035	.000
	*% Asbestos	.402[b]	.289	-.160	.000
Water Damage	*Exposed Surface	.301	-.284	.098	.000
	*Accessibility	.490[b]	.122	-.440[b]	.000
	*Activity	.275	.329[b]	-.160	.000
	*Air plenum	-.210	.021	-.098	.000
	*Friability	-.255	-.249	.045	.000
	*% Asbestos	.543[b]	-.129	-.171	.000
Exposed Surface	*Accessibility	.132	.061	-.065	.000
	*Activity	.125	-.193	.153	.000
	*Air plenum	-.695[b]	.074	.211	.000
	*Friability	.359[b]	-.059	-.098	.000
	*% Asbestos	.201	.067	.368	.000
Accessibility	*Activity	.594[b]	.348[b]	.194	-.096
	*Air plenum	-.536[b]	-.174	.301	.478
	*Friability	.522[b]	.003	-.140	.000
	*% Asbestos	.474[b]	.018	-.209	.000
Activity	*Air plenum	-.475[b]	.113	-.067	.458
	*Friability	-.493[b]	.234	-.196	.000
	*% Asbestos	.483[b]	.168	-.022	.000
Air Plenum	*Friability	.160	-.109	.098	.000
	*% Asbestos	-.429[b]	-.039	.102	.000
Friability	*% Asbestos	-.568[b]	.571[b]	.171	.000

[a] 14 observations with zero % chrysotile asbestos were deleted.

[b] P-value less than 0.05, for the test of the hypothesis that the correlation is significantly different from zero.

damage in this table include accessibility, activity, and percent asbestos. Yet the correlation between water damage and accessibility is moderately positive in the Industrial Hygienics dataset, while it is moderately negative in the Paris dataset.

Table 18 suggests that accessibility has a small positive relationship with deteriorating material conditions and water damage. In the Industrial Hygienics dataset accessibility has moderately positive relationships with activity, friability, and percent asbestos, but a moderately negative relationship with air plenums. This negative relationship is also suggested in the Battelle file, where there is slight positive relationship between accessibility and activity.

Examination of Table 18's Industrial Hygienics file suggests the existence of moderately negative correlations between activity and air plenums or friability and a moderately positive correlation between activity and percent asbestos. No comparable correlations are apparent in the Battelle or the Paris files.

Three final correlations of moderate size in Table 18 may be of interest. In the Industrial Hygienics dataset percent asbestos has a negative relationship with air plenums and friability. In the Battelle file the relationship between percent asbestos and friability is moderately positive.

An overall comparison between the correlations in the Paris dataset (both columns in Table 18) and those in the other datasets described in Tables 18 and 16 reveals that the Paris correlations are relatively small. The Paris file has the fewest number of observations, but this smaller sample size should have its largest impact upon the standard errors of the correlations, not upon the magnitude of the correlations. This disparity suggests that the Paris data were collected from different types of buildings or under different circumstances than the data collected in the United States. The few consistent intercorrelations previously noted in Table 16A are not generally confirmed in Table 18.

VI. CORRELATIONS BETWEEN THE SCORE AND ITS COMPONENTS

A. School Programs Data

Table 19 presents Spearman rank order correlations between asbestos algorithm scores and the eight components of the scores. The datasets referred

Table 19. SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM SCORES AND THE EIGHT COMPONENTS OF THE SCORES

	LOCATIONS WHERE THE DATA WERE COLLECTED						
Variable Correlated With SCORE	North Carolina (Statewide Data) N = 128[a]	Montgomery County (Ohio) N = 74	Manhattan (New York) N = 110	Staten Island (New York) N = 77	Bronx (New York) N = 130	Brooklyn (New York) N = 155	Queens (New York) N = 149
Material Condition	.632[b]	.611[b]	.412[b]	.768[b]	.645[b]	.655[b]	.537[b]
Water damage	-.024	.526[b]	.229[b]	.219	.252[b]	.065	.296[b]
Exposed surface	-.038	.000	.545[b]	.668[b]	.737[b]	.420[b]	.728[b]
Accessibility	.407[b]	.092	.581[b]	.642[b]	.718[b]	.524[b]	.586[b]
Activity	.248[b]	.240[b]	.686[b]	.377[b]	.624[b]	.373[b]	.744[b]
Air plenum	-.073	.228	.268[b]	.212	-.185[b]	.211[b]	.352[b]
Friability	.894[b]	.763[b]	-.223[b]	.022	.201[b]	.521[b]	-.128
% Asbestos	.813[b]	.085	.017	.311[b]	.044	.474[b]	-.285[b]

[a]The conditions deleting certain observations are described in the footnotes attached to Table 2.

[b]P-value less than 0.05, for the test of the hypothesis that the correlation is significantly different from zero.

to in this table are identical with the datasets referred to in Tables 2 and 16. Examination of Table 19 reveals that deteriorating material conditions and high activity are positively related to the score in each dataset (7/7), while accessibility is positively related in six datasets (6/7). Water damage, exposed surfaces, and air plenums are positively related to the score in five different datasets (5/7). Friability is positively related to the score in four datasets (4/7), while percent asbestos is positively related in only three datasets (3/7).

The relatively consistent relationship between the score and six of the eight component variables (material condition, activity, accessibility, water damage, exposed surface, and air plenum) is not surprising given the procedure for estimating the score. In contrast, the relatively inconsistent relationship between the score and friability or percent asbestos is surprising given the scoring procedure and the conceptual importance of these two score components.

B. Friability

Inspection of Table 19 reveals that friability is negatively correlated with the score in the Manhattan dataset and, possibly, in the Queens dataset, while there is no correlation between these variables in the Staten Island dataset. An examination of the Manhattan, the Queens, and the Staten Island friability distributions in Table 2 reveals that in these three datasets there are few observations with a friability code of "2." This lack of "2" codes lends a "bimodal" aspect to each of the friability distributions in the three datasets. The bimodal aspect of the friability distributions in the Manhattan, the Queens, and the Staten Island files may be related to, or responsible for, the inconsistent friability correlations noted in Table 19.

C. Percent Asbestos

Inspection of Table 19 suggests that percent asbestos is negatively correlated with the score in the Queens dataset, while there appears to be no percent asbestos/score correlation in the Montgomery County, the Manhattan, and the Bronx datasets. An examination of the Queens percent asbestos distribution in Table 2 reveals that the majority of the observations received a percent asbestos code of "3." Yet in each of the datasets where there is a positive association between percent asbestos and the score, the most frequently assigned percent asbestos code is "2." The assignment of "3's" instead of "2's" may account for the negative association with the score in

the Queens file. An examination of the Montgomery County and the Bronx percent asbestos distributions in Table 2 reveals that in these datasets only two of the three available codes were assigned. The corresponding reduction in percent asbestos variation in these datasets may account for the lack of an association with the score which was noted in the Montgomery County and the Bronx files. Inspection of the Manhattan file in Table 2 reveals that percent asbestos codes are approximately evenly divided among the three possibilities. Hence, a possible explanation of the zero score/percent asbestos correlation is less obvious.

D. Acoustical Tile Deletion Effects

Table 20 also presents Spearman rank order correlations between algorithm scores and algorithm variables, but acoustical tile observations have been deleted. Table 20 is based upon the New York datasets, which were previously described in Tables 3 and 17. Inspection of Table 20 suggests that five of the algorithm variables (material condition, water damage, exposed surface, accessibility, and activity) are positively correlated wit. the algorithm score in each New York file; one variable (air plenum) has a slight negative correlation in the Bronx file; and two variables (friability and percent asbestos) are inconsistently correlated with the algorithm score across all files.

The patterns of friability/score correlations and percent asbestos/score correlations in Tables 19 and 20 are essentially identical. The one exception is the Manhattan percent asbestos/score relationship. In Table 19 this correlation is very slightly positive, while in Table 20 this correlation is moderately negative. The general similarity of the New York correlations in Tables 19 and 20 supports the hypothesis that the inconsistent correlations in Table 19 are not a function of the acoustical tile observations.

E. Correlations in the Industrial Hygienics, the Battelle, and the Paris Datasets

Table 21 presents rank order correlations between algorithm scores and algorithm variables derived from the Industrial Hygienics, the Battelle, and the Paris datasets. Inspection of Table 21 reveals patterns of correlations differing from those described in Tables 19 and 20. In the Industrial Hygienics file these differences include the very small material condition/score correlation, and the negative water damage, accessibility, activity, and air plenum correlations. In the Battelle file, the small water damage/score

Table 20. SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM SCORES AND THE EIGHT COMPONENTS OF THE SCORES: ACOUSTICAL TILE OBSERVATIONS DELETED[a]

Variable Correlated With Score	New York Data Sources				
	Manhattan N=35	Staten Island N=65	Bronx N=77	Brooklyn N=81	Queens N=96
Material Condition	.880[b]	.824[b]	.686[b]	.860[b]	.638[b]
Water Damage	.455[b]	.209	.248[b]	.293[b]	.413[b]
Exposed Surface	.905[b]	.817[b]	.925[b]	.874[b]	.885[b]
Accessibility	.933[b]	.776[b]	.832[b]	.750[b]	.751[b]
Activity	.949[b]	.546[b]	.746[b]	.656[b]	.840[b]
Air Plenum	.420[b]	.247[b]	-.115	.433[b]	.435[b]
Friability	-.327	.000	.746[b]	.550[b]	-.152
% Asbestos	-.552[b]	.329[b]	.000	.326[b]	-.477[b]

[a] Deleted observations are described in the footnotes attached to Table 3.

[b] P-value less than 0.05, for the test of the hypothesis that the correlation is significantly different from zero.

Table 21. SPEARMAN RANK ORDER CORRELATIONS BETWEEN ASBESTOS ALGORITHM SCORES AND THE EIGHT COMPONENTS OF THE SCORES

Variable Correlated With SCORE	Data Sources: Industrial Hygienics (Northeast)	Battelle (Ohio)	Paris (France)	Paris[a] (France)
	N = 40	N = 40	N = 23	N = 9
Material Condition	.098	.656[b]	-.050	.550
Water Damage	-.049	.016	-.164	.000
Exposed Surface	.548[b]	-.097	.354	.000
Accessibility	-.189	.154	-.170	.175
Activity	-.080	.487[b]	.049	.373
Air Plenum	-.306	.040	.206	.577
Friability	.672[b]	.860[b]	.164	.000
% Asbestos	.009	.660[b]	.962[b]	.000

[a] 14 observations with zero % chrysotile were deleted.

[b] P-value less than 0.05, for the test of the hypothesis that the correlation is significantly different from zero.

correlation and the negative exposed surface correlation are surprising. In the Paris file (N=23), the unexpected correlations include the negative material condition, water damage, and accessibility statistics. It should be pointed out that the weakly negative material condition in the Paris file (N=23) becomes moderately positive (N=9) when observations with 0 percent chrysotile in the bulk sample are deleted. The zero correlations in the reduced Paris file (N=9) are caused by zero variances associated with the respective algorithm variables. Friability is positively associated with the algorithm score in the Industrial Hygienics, the Battelle, and the Paris datasets (N=23), but percent asbestos is meaningfully related to the score only in the Battelle and the Paris datasets (N=23).

Simultaneous consideration of the 10 datasets in Tables 19 and 21 confirms the impression that material condition and activity are positively associated with the algorithm score. The variables: exposed surface, air plenum, friability, and percent asbestos also receive some additional support for positive associations with the algorithm score. But the score/water damage and the score/accessibility correlations noted in Table 19 get no support in Table 21.

VII. RELATIONSHIPS BETWEEN THE ALGORITHM VARIABLES AND VARIOUS DEPENDENT VARIABLES

The multivariable analyses summarized in this section utilize several different surrogate dependent variables because suitable airborne asbestos data were not available. Hence, these analyses are not definitive. Rather, they are suggestive of the type of analyses which should be done when adequate airborne asbestos data are available. In addition, these analyses do not compensate for possible differences in the materials of interest in various regions of the country, nor do they compensate for known differences in data collection protocols that could distort comparisons between analyses. Specifically, the possibility of selection bias introducted by nonuniform sampling procedures must be acknowledged when these data are cited.

A. School Programs Data

Table 22 summarizes a series of discriminant analyses of algorithm scores. The datasets presented in Table 22 correspond to the datasets presented in Tables 2, 7, 16, and 19. In Table 19 the relationship between each

Table 22. DISCRIMINANT ANALYSES OF ASBESTOS ALGORITHM SCORES[a]

Independent Variables	LOCATIONS WHERE THE DATA WERE COLLECTED: North Carolina (Statewide Data)	Montgomery County (Ohio)	Manhattan (New York)	Staten Island (New York)	Bronx (New York)	Brooklyn (New York)	Queens (New York)
N = (% GSCORE=1)	128 (55.5)	74 (83.8)	110 (28.2)	77 (54.5)	130 (38.5)	155 (47.1)	149 (41.6)
All 8 Variables[b]	---	---	---	---	---	---	---
% Observations Classified Correctly[e]	96.09	90.54[d]	100.00	94.81	91.54	91.61	96.64
Best 4 Variables[c]	PERABS, FRIB, ACC, WATDAM	PERABS, COND, ACC, FRIB	EXPSUR, PERABS, COND, ACT	EXPSUR, FRIB, WATDAM, PLEN	EXPSUR, PERABS, COND, FRIB	EXPSUR, PERABS, COND, FRIB	EXPSUR, PERABS, ACC, ACT
% Observations Classified Correctly	95.31	91.89	99.09	94.81	89.23	87.74	96.64
Best 3 Variables	PERABS, FRIB, ACC	PERABS, FRIB, WATDAM	EXPSUR, PERABS, COND	EXPSUR, FRIB, WATDAM	EXPSUR, PERABS, COND	EXPSUR, FRIB, COND	EXPSUR, PERABS, ACT
% Observations Classified Correctly	95.31	90.54	98.18	90.91	89.23	87.74	91.28
Best 2 Variables	PERABS, FRIB	FRIB, ACC	PERABS, COND	EXPSUR, WATDAM	ACC, ACT	FRIB, COND	EXPSUR, PERABS
% Observations Classified Correctly	93.75	87.84	78.18	89.61	84.62	81.94	84.56

[a]The dependent variable (GSCORE) = 0, if SCORE < 15, otherwise dependent variable = 1. The measure of generalized squared distance (D^2) was based upon the pooled covariance matrix. Prior probabilities of group membership (GSCORE) were assumed to be equal.

[b]Material condition (COND), water damage (WATDAM), exposed surface (EXPSUR), accessibility (ACC), activity (ACT), air plenum (PLEN), friability (FRIB), % asbestos (PERABS).

[c]Best models were selected by a stepwise regression (discriminant procedure, such that the $R^2(D^2)$ statistic (for the dichotomized SCORE variable) was maximized.

[d]This model only includes 7 variables because EXPSUR has no variation.

[e]50% of the observations can be correctly classified by "tossing" an unbiased coin.

algorithm variable and the algorithm score was characterized. In Table 22 the relationship between the score and a set of algorithm variables is characterized. The purpose of the Table 22 analyses was to identify those algorithm variables which are the best predictors of high or low algorithm scores. A "cutpoint" of 15 was used to identify high and low scores because this value is near the median score in five of the seven datasets analyzed. This value also separates the first two score intervals in Table 7 from the other intervals.

Table 22 indicates that at least 90 percent of the observations in each dataset were successfully classified as "high" or "low" by four algorithm variables, but the four best predictors are not the same in each dataset. Moreover, the apparently large percentages of correctly classified observations should be evaluated in the context of alternative procedures for classifying the observations. Specifically, 50 percent of the observations in each dataset could be correctly classified by "tossing" an unbiased coin. Alternatively, it could be assumed that all observations in each dataset belong to the "high score" category (GSCORE=1). The effect of this assumption in the Montgomery County dataset would be to correctly classify 84 percent of the available observations, while in the Manhattan dataset this assumption would correctly classify 28 percent of the available observations [see (% GSCORE =1) in Table 22].

A comparison of the best four variable models (Table 22) reveals that the most frequently selected variables included percent asbestos (6/7), friability (5/7), and exposed surface (5/7). The least selected variables included air plenum (1/7), water damage (2/7), and activity (2/7). Material condition (4/7) and accessibility (3/7) fell between the two extremes. Similar comparisons of the best three- and two-variable models reveals that percent asbestos, friability, and exposed surfaces continue to be the better score predictors.

Tables 23-26 are based upon the North Carolina, the Montgomery County, the New York City, and the Battelle files respectively. Different dependent variables were employed in the analyses of these datasets because data concerning the same dependent variables were not consistently available in all of these datasets. A given variable was designated "the dependent variable" in an analysis if there was some basis for assuming that the dependent variable designate is predictive of airborne asbestos levels. Generally, the designated

Table 23. MULTIVARIABLE MODELS WITH DIFFERENT DEPENDENT VARIABLES: NORTH CAROLINA FILE

	Dependent Variables				
Independent Variables	Material Type (SOFTM)[a]	Priority of Repair (FIX)[b]	Method of Repair (REMOVE)[c]	Score Dichotomy (GSCORE)[d]	Score Continuous (SCORE)[e]
N = (% Dep. Var. = 1)	109[f] (49.5)	99[g] (58.6)	57[h] (45.6)	128 (55.5)	128
All 8 Variables[i]	-----	-----	-----	-----	----- $R^2 = .92$
% Observations Correctly Classified	74.31	73.73	92.98	96.09	-----
Best 4 Variables[j]	ACT, PLEN, FRIB, PERABS	COND, WATDAM, ACC, FRIB	ACC, ACT, FRIB, PERABS	PERAB, FRIB, ACC, WATDAM	COND, ACT, FRIB, PERABS $R^2 = .90$
% Observations Correctly Classified	77.06	74.75	91.23	95.31	-----
Best 3 Variables	ACT, PLEN, FRIB	WATDAM, ACC, FRIB	ACC, FRIB, PERABS	PERABS, FRIB, ACC	COND, FRIB, PERABS $R^2 = .88$
% Observations Correctly Classified	77.06	69.70	91.23	95.31	-----
Best 2 Variables	ACT, FRIB	COND, FRIB	COND, PERABS	PERABS, FRIB	COND, FRIB $R^2 = .83$
% Observations Correctly Classified	77.06	68.69	92.98	93.75	-----
Best 1 Variable	FRIB	FRIB	PERABS	FRIB	FRIB $R^2 = .72$
% Observations Correctly Classified	60.55	69.70	87.72	93.75	-----

[a] Discriminant analyses, dependent variable (SOFTM) is presence or absence of soft accoustics.

[b] Discriminant analyses, dependent variable (FIX) is recommendation to repair or defer.

[c] Discriminant analyses, dependent variable (REMOVE) is recommendation to remove or paint over.

[d] Discriminant analyses, dependent variable (GSCORE) is dichotomized SCORE, see Table 22.

[e] Regression analyses, dependent variable (SCORE) is the asbestos algorithm score.

[f] 19 Observations deleted by missing values for SOFTM.

[g] 29 Observations deleted by missing values for FIX.

[h] 71 Observations deleted by missing values for REMOVE.

[i] See footnote b, Table 22.

[j] See footnote c, Table 22.

Table 24. MULTIVARIABLE MODELS WITH DIFFERENT DEPENDENT VARIABLES: MONTGOMERY COUNTY FILE

	Dependent Variables		
Independent Variables	Method of Repair (REMOV2)[a]	Score Dichotomy (GSCORE)[b]	Score Continuous (SCORE)[c]
N =	43[d]	74	74
(% Dep. Var. = 1)	(46.5)	(83.8)	-----
All 7 Variables[e]	-----	-----	-----
			R^2 = .95
% Obs. Correctly Classified	100.0	90.54	-----
Best 4 Variables	COND, ACC FRIB, PERABS	PERABS, COND, ACC, FRIB	COND, ACT, PLEN, FRIB
			R^2 = .89
% Obs. Correctly Classified	100.0	91.89	-----
Best 3 Variables	COND, ACC, FRIB	PERABS, FRIB, WATDAM	COND, ACT, FRIB
			R^2 = .85
% Obs. Correctly Classified	100.00	90.54	-----
Best 2 Variables	COND, FRIB	FRIB, ACC	COND, FRIB
			R^2 = .83
% Obs. Correctly Classified	90.70	87.84	-----
Best 1 Variable	COND.	FRIB.	FRIB.
			R^2 = .62
% Observations Correctly Classified	88.37	77.03	-----

[a]Discriminant analyses, dependent variable (REMOV2) is recommendation to remove or to defer abatement.

[b]Discriminant analyses, dependent variable (GSCORE) is dichotomized SCORE, see Table 22.

[c]Regression analyses, dependent variable (SCORE) is the asbestos algorithm score.

[d]31 Observations were deleted by missing values for variable REMOV2.

[e]EXPSUR has no variation, consequently it was deleted from all models.

Table 25. DISCRIMINANT ANALYSES OF MATERIAL TYPE (SOFTM)[a]: NEW YORK FILES[b]

Independent Variables	Manhattan (New York)	Bronx (New York)	Brooklyn (New York)	Queens (New York)
N = (% SOFTM = 1)	83[c] (9.64)	63[d] (15.87)	100[e] (26.00)	53[f] (20.75)
All 8 Variables	--------[g]	--------[g]	--------[g]	--------[g]
% Observations Correctly Classifed	87.95	98.41	99.00	94.34
Best 4 Variables	ACC, PLEN FRIB, PERABS	ACT, PLEN FRIB, PERABS	COND, PLEN FRIB, PERABS	COND, WATDAM PLEN, FRIB
% Observations Correctly Classified	87.95	96.83	99.00	94.34
Best 3 Variable	PLEN, FRIB, PERABS	ACT, FRIB, PERABS	COND, FRIB, PERABS	COND, PLEN, FRIB
% Observations Correctly Classified	87.95	96.83	100.00	94.34
Best 2 Variables	FRIB, PERABS	FRIB, PERABS	FRIB, PERABS	COND, FRIB
% Observations Correctly Classified	86.75	100.00	100.00	94.34
Best 1 Variable	FRIB	FRIB	FRIB	FRIB
% Observations Correctly Classified	86.75	100.00	100.00	94.34

[a] SOFTM = 1, if soft accoustics were present, SOFTM = 0 otherwise.

[b] SOFTM had no variation in Staten Island.

[c] 27 observations were deleted by missing values on SOFTM.

[d] 67 observations were deleted by missing values on SOFTM.

[e] 55 observations were deleted by missing values on SOFTM.

[f] 96 observations were deleted by missing values on SOFTM.

[g] EXPSUR had no variation.

Table 26. REGRESSION ANALYSES OF STIMULATED FIBER-RELEASABILITY MEASUREMENTS[a]

Independent Variables	Coded % Asbestos Allowed to Enter Model	Uncoded % Asbestos Allowed to Enter Model
All 8 Variables[b]	--------	--------
R^2 =	.555	.637
Best 4 Variables	COND, ACC, FRIB, PLEN	COND, ACC, ASBES, PLEN
R^2 =	.550	.608
Best 3 Variables	ACC, FRIB, PLEN	ACC, PLEN, ASBES
R^2 =	.484	.575
Best 2 Variables	FRIB, PLEN	PLEN, ASBES
R^2 =	.436	.497
Best 1 Variable	FRIB	ASBES
R^2 =	.369	.439

[a] Battelle data, N = 40, dependent variable = LOG_e (Stimulated Fiber-Releasibility Measurements)

[b] Material condition (COND), water damage (WATDAM), exposed surface (EXPSUR), accessibility (ACC), activity (ACT), air plenum (PLEN), friability (FRIB), and coded % asbestos (PERABS) or uncoded % asbestos (ASBES).

dependent variables are based upon abatement recommendations, the algorithm score, a building characteristic, or air sampling. The basis for the abatement recommendations on the North Carolina file is not known. However, the abatement recommendations on the Montgomery County file are based upon the algorithm score and values of five key algorithm variables--friability, water damage, material condition, and accessibility.

B. North Carolina Data

In Table 22 the dichotomized algorithm score is the dependent variable. In Table 23, four new dependent variables are considered along with the dichotomized score variable in the context of the North Carolina dataset. These new dependent variables include the presence or absence of soft acoustics (SOFTM), a recommendation to repair or defer (FIX), a recommendation to remove or paint over asbestos-containing materials (REMOVE), and the continuous algorithm score (SCORE). Examination of the best four, three, two, and one variable models indicates that the compositions of best four, three, or two variables models are a function of the dependent variable employed, despite the fact that all of these dependent variables should be predictive of airborne asbestos levels. The one consistency in Table 23 is that friability appears in 18 of the 20 models displayed. The two exceptions are models involving the dependent variable REMOVE. This dependent variable appears to have a stronger relationship to percent asbestos.

C. Montgomery County Data

In Table 24, the dependent variables include a recommendation to remove asbestos-containing materials or to defer abatement (REMOV2), the dichotomized score variable (GSCORE), and the continuous algorithm score (SCORE). These three variables were the only reasonable dependent variables available in the Montgomery County dataset. Examination of the best three-, two-, and one-variable models indicates that the compositions of these models are a function of the dependent variables employed. It is of interest that friability appears in 11 of the 12 models displayed and that the best four-variable models for REMOV2 and GSCORE are identical. The best four-variable model for SCORE probably differs from the corresponding GSCORE model because information was lost when the algorithm score was dichotomized. Consideration should also be given to the effect of the GSCORE cutpoint upon the algorithm variables included in the best four variable model.

D. New York City Data

Table 25 summarizes a final series of discriminant analyses of data contained in the New York files. The dependent variable (SOFTM) refers to the presence or absence of soft acoustical materials. It may be of interest that friability appears in all 16 of the displayed models and that percent asbestos appears in 9 of the models. Yet the inclusion of the friability variable in all 16 of the displayed models should not be surprising because friable materials are "soft" materials by definition. It also should be noted that the best Bronx four-variable model is identical to the corresponding North Carolina model (Table 23). Finally, the best Manhattan and the best Brooklyn four-variable models are very similar to the best Bronx four-variable model. In the Manhattan file accessibility has replaced activity (which is in the Bronx model), while in the Brooklyn file activity is replaced by material condition.

E. Battelle Data

Table 26 presents two series of regression analyses of stimulated fiber-releasability measurements from the Battelle dataset. In the first series bulk sample analytical results were coded in the manner prescribed by the asbestos algorithm (PERABS), while in the second series bulk sample results were left uncoded (ASBES). Inspection of Table 26 reveals that categorizing (coding) bulk sample analytical results allows friability instead of percent asbestos to be selected for the best four-, three-, two-, and one-variable models. If bulk sample analytical results are not arbitrarily coded, then they replace the friability variable in every model.

F. Comments Concerning the Multivariable Analyses

The multivariable analyses summarized in Tables 22-26 are not definitive in any sense of the word. Rather, these analyses are suggestive of the types of analyses that should be done when suitable airborne asbestos data are available. All of the dependent variables referred to in Tables 22-26 could be considered to be surrogate airborne asbestos variables, but there is at present no scientific basis suitable for selecting one of the surrogates as superior to the others. The stimulated fiber-releasability measurements have a unique appeal because they do represent a type of airborne asbestos. Yet these data cannot be fairly used to evaluate the algorithm because of the manner in which they were collected. It is possible that Battelle's fiber releasability protocol could be modified so that this type of data could be used to develop an empirical asbestos exposure score.

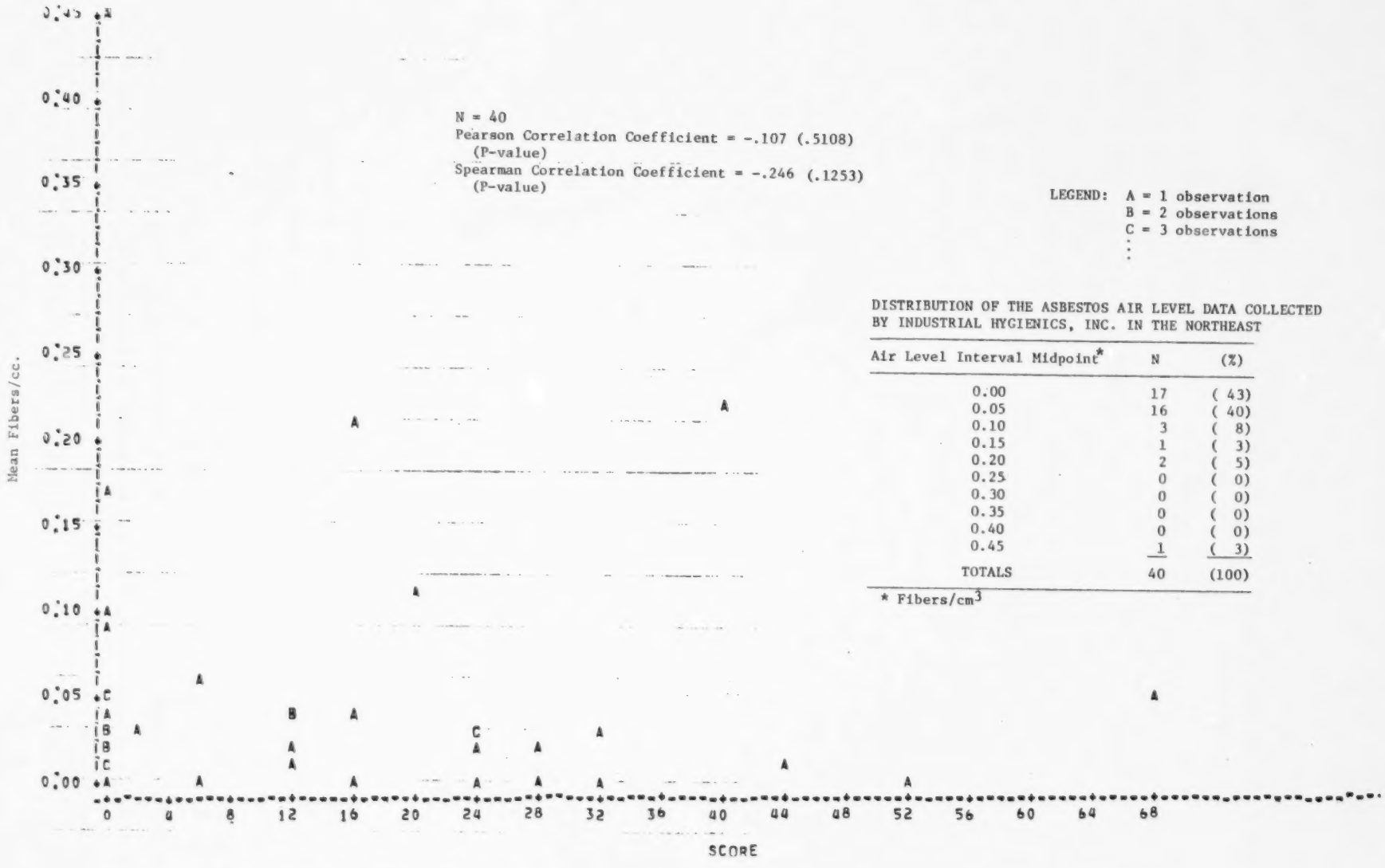
G. Plots Characterizing the Relationship Between the Score and Asbestos Air Level Data

Figure 1 contains a plot of mean fiber concentrations in air samples versus the algorithm score, which is based upon information in the Industrial Hygienics dataset. Because the air samples were analyzed by phase contrast microscopy, it cannot be assumed that all of the fibers detected are asbestos fibers. It also should be noted that the algorithm score distribution in the Industrial Hygienics file (Table 9) is more skewed than six of the seven score distributions in Table 7 and that one or two air level outliers may be dominating the correlation. Thus, the negative correlation in Figure 1 may or may not be biased.

Figures 2 and 3 are plots of airborne asbestos (chrysotile) data versus the algorithm score derived from the Paris dataset. The air samples were analyzed by transmission electron microscopy. In Figure 2 the "unlogged" information is shown, while in Figure 3 both the scores and the air levels have been transformed by taking logarithms to base e. It should be noted that 14 (chrysotile) observations with algorithm scores of zero have been deleted from Figure 3. The nine observations in Figure 3 are the same nine observations referred to in Tables 18 and 21. It may be of interest that the correlation in Figure 2 is weakly negative, while the correlation in Figure 3 is weakly positive. It should be recalled that the Paris air level measurements are based upon transmission electron microscopy, which does distinguish asbestos fibers from nonasbestos fibers.

Figures 4-7 are plots of stimulated fiber releasability data versus algorithm scores derived from the Battelle dataset. Figure 4 contains a plot of fiber releasability levels (VAIR) versus the original algorithm score (SCORE). In Figure 5 both VAIR and SCORE have been transformed by taking logarithms to base e. In Figure 6 SCORE has been replaced by SCOR2. SCOR2 is identical to the original algorithm score except that bulk sample analytical results are uncoded (see Table 11). In Figure 7 both VAIR and SCOR2 have been transformed by taking logarithms to base e.

It is of interest that each of the correlations in Figures 4-7 is of at least moderate size. The correlation in Figure 7 might even be interpreted as indicating a strong positive relationship between logged fiber releasability levels and logged modified scores. In their March 1980 report, Patton et al. (1980) indicate that both friability and percent asbestos are positively



DISTRIBUTION OF THE ASBESTOS AIR LEVEL DATA COLLECTED BY INDUSTRIAL HYGIENICS, INC. IN THE NORTHEAST

Air Level Interval Midpoint*	N	(%)
0.00	17	(43)
0.05	16	(40)
0.10	3	(8)
0.15	1	(3)
0.20	2	(5)
0.25	0	(0)
0.30	0	(0)
0.35	0	(0)
0.40	0	(0)
0.45	1	(3)
TOTALS	40	(100)

* Fibers/cm^3

Figure 1. Plot of Mean Fiber Concentrations (Determined by Phase Contrast Microscopy) Versus the Asbestos Algorithm Score: Industrial Hygienics Dataset

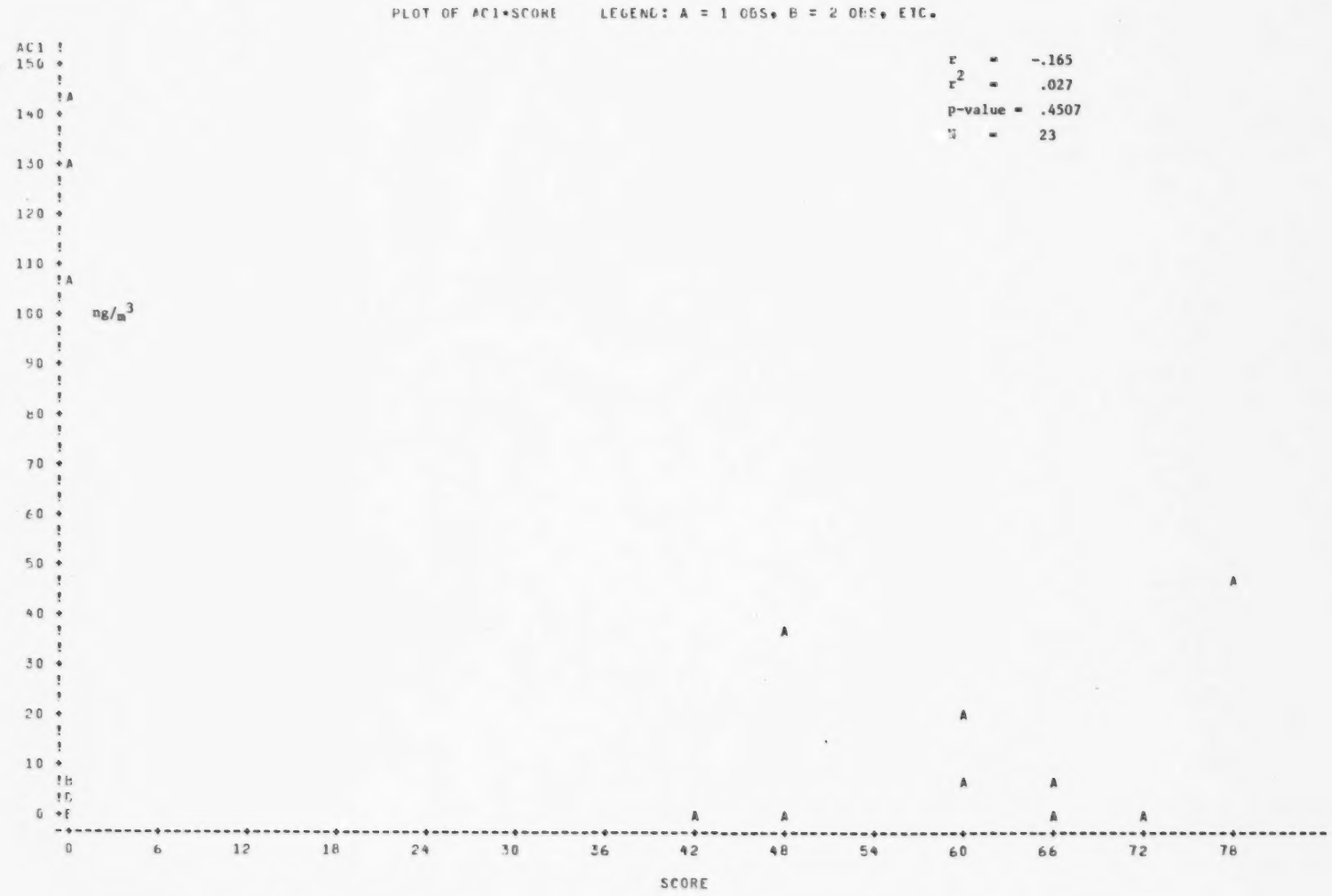


Figure 2. Plot of Air Chrysotile Levels (AC1) Versus the Asbestos Algorithm Score (SCORE).: Paris Dataset

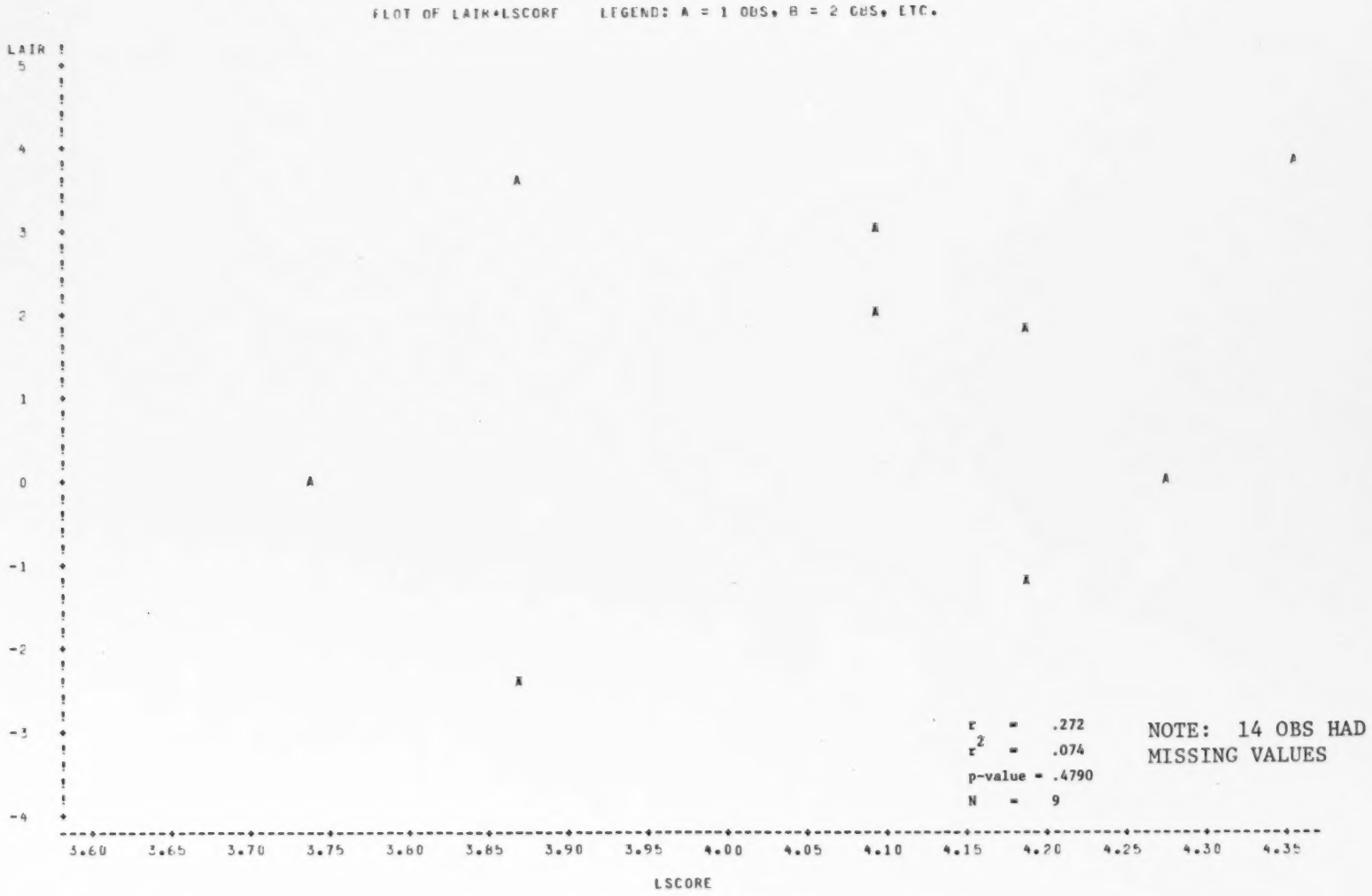


Figure 3. Plot of LOG_e (Air Chrysotile Levels), (LAIR) versus LOG_e (Asbestos Algorithm Score), (LSCORE): Paris Dataset

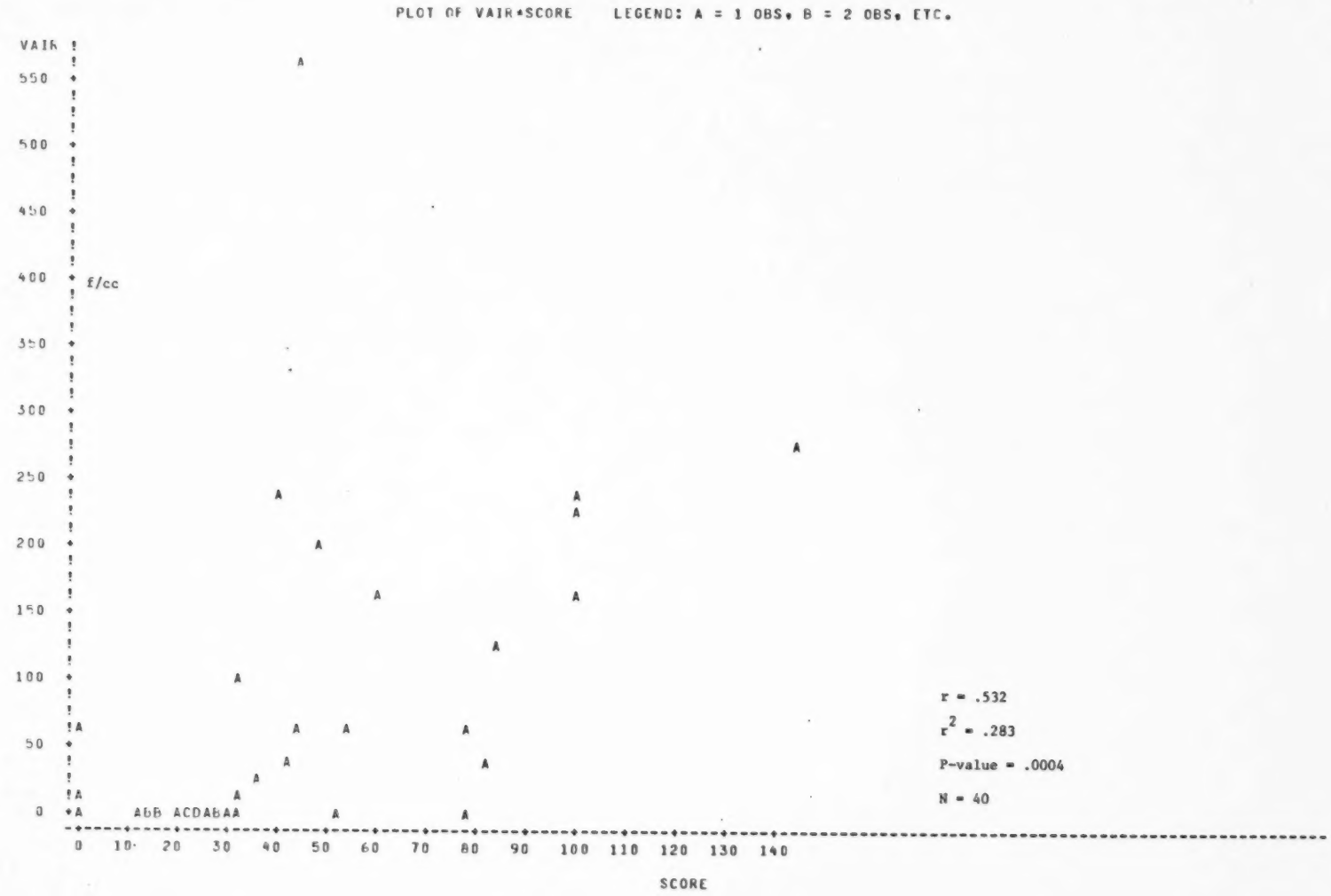


Figure 4. Plot of Stimulated Fiber Releasability (VAIR) versus the Asbestos Algorithm Score (SCORE): Batelle Dataset

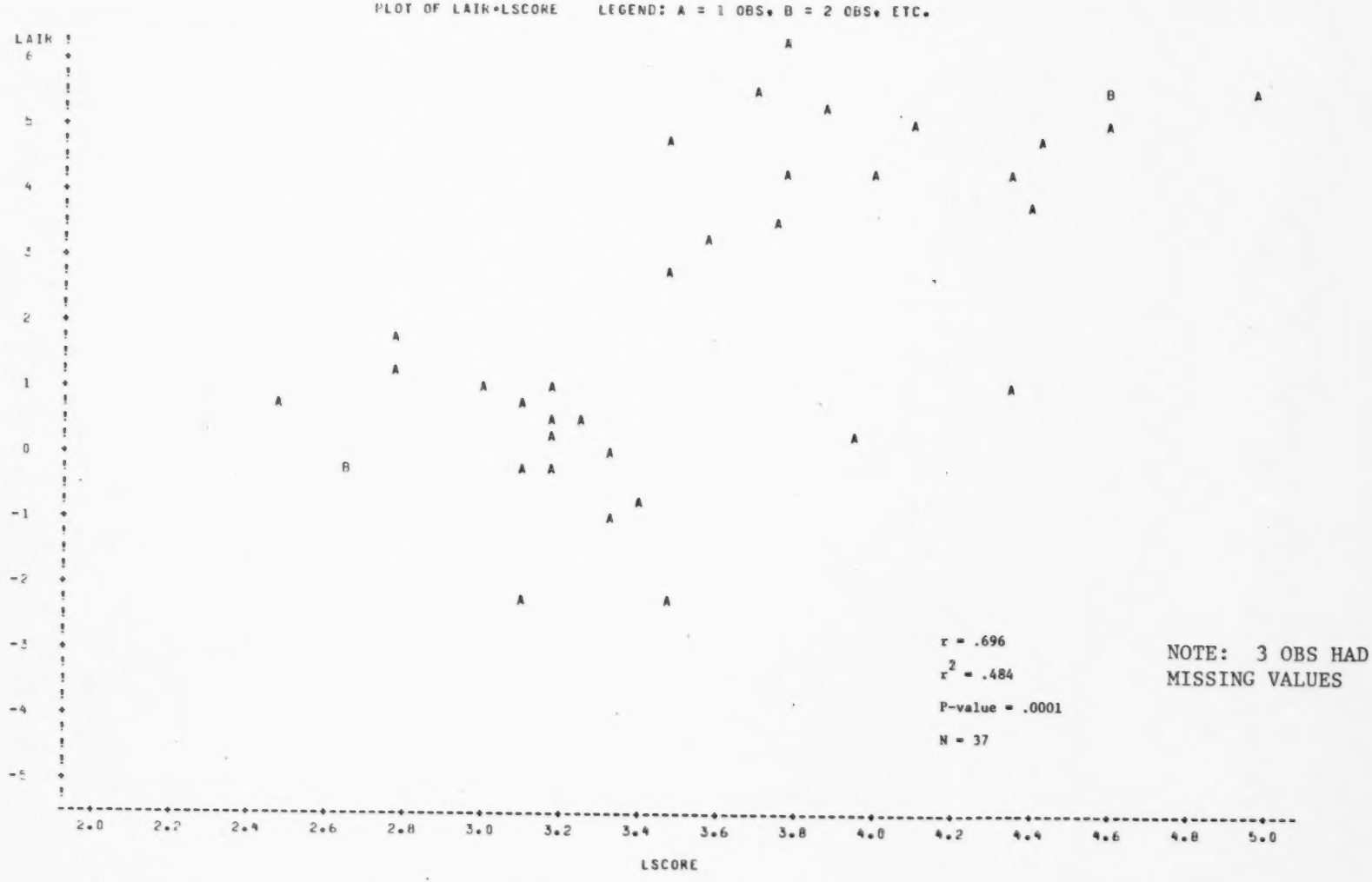


Figure 5. Plot of LOG_e (Stimulated Fiber-Releasability), (LAIR), versus LOG_e (Asbestos Algorithm Score), (LSCORE): Battelle Dataset

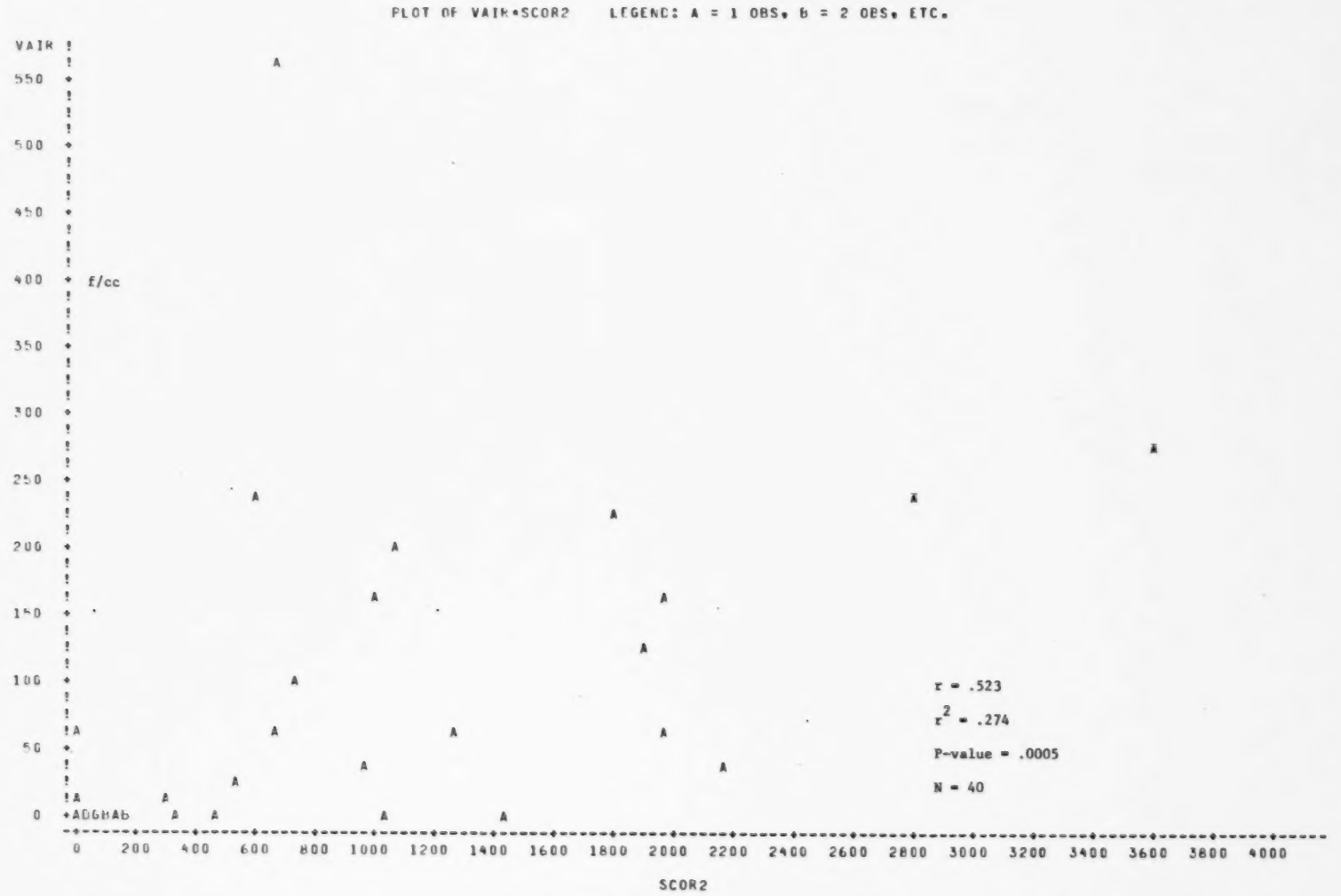


Figure 6. Plot of Stimulated Fiber-Releasability (VAIR) versus the Modified Algorithm Score (SCOR2): Battelle Dataset

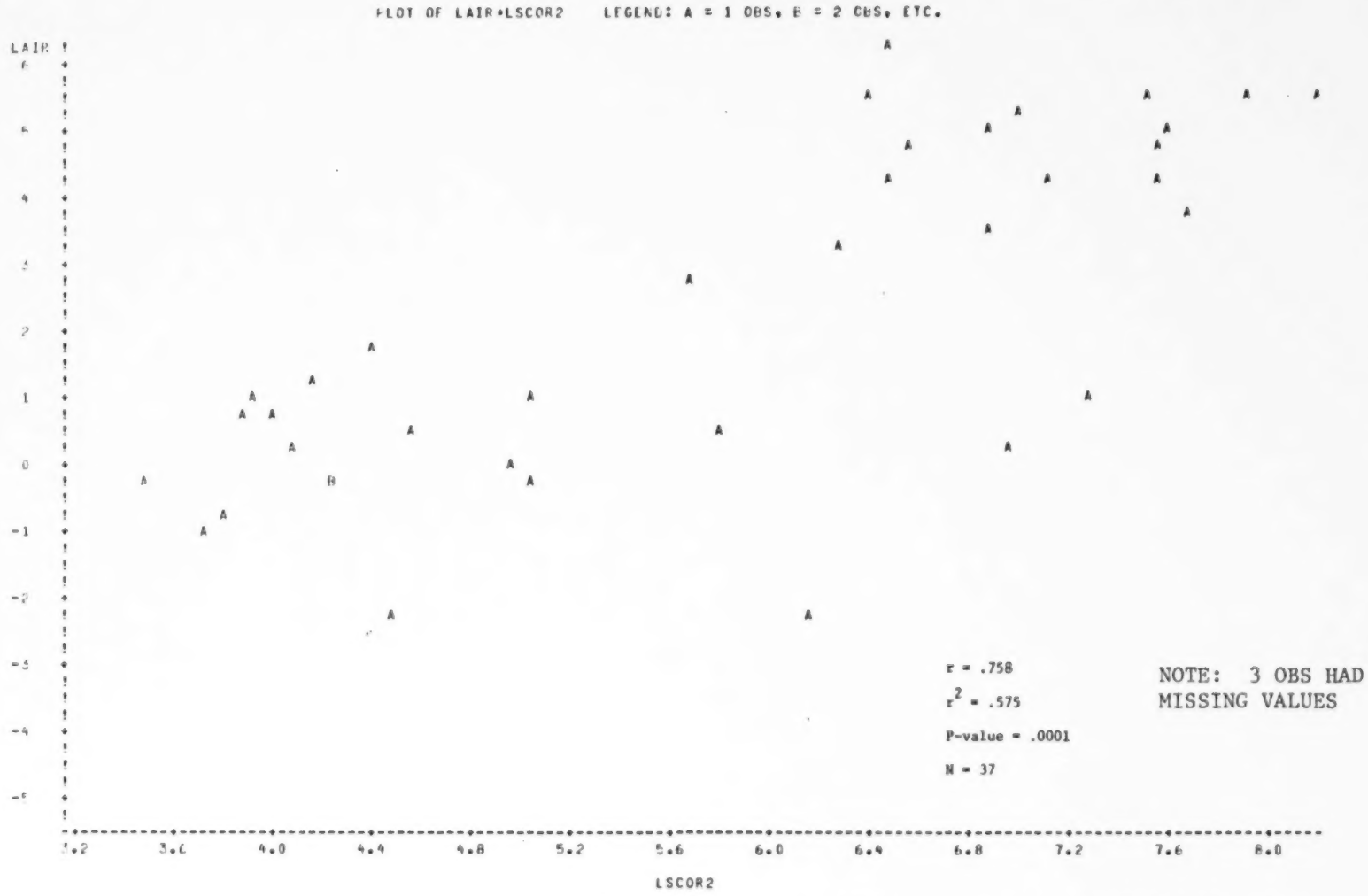


Figure 7. Plot of LOG_e (Stimulated Fiber-Releasability), (LAIR), versus LOG_e (Modified Algorithm Score), (LSCOR2): Battelle Dataset

related to fiber releasability levels. Thus, the associations displayed in Figures 4-7 should not be surprising. Nevertheless, Figures 4-7 are suggestive of the type of airborne asbestos-exposure score relationship that could be estimated in a well-designed air-sampling survey.

VIII. CONCLUSIONS

A. Variable Distribution Summary

A comparison of algorithm variable distributions reveals that the eight variables can be ordered in terms of the consistency of frequency distributions across datasets. Specifically, if the same algorithm variable code was more frequently selected (by raters) in different locations, then the data from different locations were considered "consistent." However, it must be recognized that different materials may have been examined in each of the locations providing algorithm data, and that different sampling protocols were followed when sites were selected. Hence the consistency data should not be interpreted as rating reliability data. The water damage variable is the most consistent. The remaining variables ordered from high to low consistency across datasets are exposed surface, air plenum, material condition, percent asbestos, accessibility, and friability. "0" is the most frequently selected water damage, air plenum, and material condition code; "4" is the most frequently selected exposure surface code; "2" is the most frequently selected friability and percent asbestos code; and "1" is the most frequently selected accessibility and activity code.

If an algorithm score cutpoint of 25 is assumed, then it appears that the New York City and the Industrial Hygienics observations have the lowest scores because between 70 and 90 percent of the observations are below this cutpoint. In the Montgomery County and the Battelle datasets only 39 to 40 percent of the observations are below it. The selection of alternative cut-points can change the relative ranking of datasets in terms of the frequency of high scores. It also should be noted that this ranking may be affected by slight differences in the algorithm variable coding rules used in each location providing data.

The airborne fiber concentration measurements obtained by Industrial Hygienics are all less than 0.50 fibers per cubic centimeter. It cannot be assumed that all of these fibers are asbestos fibers. Fifty percent of the

airborne fiber concentration measurements obtained by Battelle are greater than 5.00 fibers per cubic centimeter. These higher concentrations are a function of mechanical vibration in an enclosed space. Fifty percent of the asbestos mass concentration observations collected in Paris are below 3.0 nanograms per cubic meter. Outside air samples, analyzed in a similar manner, suggest that the background mass concentration may be between five and seven nanograms per cubic meter.

B. Algorithm Variable Intercorrelation Summary

Different patterns of intercorrelations are evident in the data available from the asbestos-in-schools programs and in the data collected by Battelle, Industrial Hygienics, and the EPA (Paris). In the schools program data the percent asbestos/friability correlation is moderately positive, but the remaining percent asbestos correlations are generally small. The small to moderately negative friability/accessibility correlation may also be of interest. Finally, material condition has moderately positive correlations with accessibility and exposed surfaces, while exposed surfaces have moderately positive correlations with accessibility and activity.

C. Score/Component Correlation Summary

In the schools program data, six algorithm variables have relatively consistent positive associations with the algorithm score. The two exceptions are friability and percent asbestos, the theoretically more important variables. Detailed analysis supports the hypothesis that these inconsistencies are not a function of acoustical tile observations in the New York datasets.

D. Algorithm Variable--Dependent Variable Summary

Discriminant analyses of the dichotomized algorithm score in the schools program datasets were completed. A comparison of the best four variable models reveals that the most frequently selected variables included percent asbestos, friability, and exposed surface.

In the North Carolina dataset the impact of different dependent variables assumed to be related to airborne asbestos levels was explored. The variable friability appeared in 18 of the 20 models considered. A similar phenomenon was observed in the Montgomery County and the New York files.

In the Battelle dataset stimulated fiber-releasability measurements were regressed upon algorithm data. Categorizing bulk sample analytical results allows friability, instead of percent asbestos, to be selected for the best four-, three-, two-, and one-variable models. If bulk sample analytical

results are not arbitrarily coded, then bulk sample analytical results replace the friability variable in every model.

E. Algorithm Score--Airborne Asbestos Summary

The Industrial Hygienics plot of the mean fiber concentrations versus the algorithm score suggests that either there is no relationship between the two variables or that the relationship is negative. Yet there are several reasons why this conclusion may not be justified. The air samples were analyzed by a relatively insensitive procedure, the score distribution is skewed, and one or two air-level outliers may be dominating the relationship. The mass concentration--score plots derived from the Paris dataset also cannot be considered definitive. Sixty percent of the relatively small number of observations collected in Paris are from sites where there was essentially no asbestos in the friable material.

The Battelle plots of stimulated fiber concentrations versus the algorithm score suggest that there is a moderately strong relationship between the two variables. Yet most score components (air plenum, water damage activity, accessibility, and exposed surface) are not relevant to the stimulated fiber concentration measurements because of the manner in which they were taken. Thus the Battelle plots cannot be considered definitive in terms of indicating the algorithm score's measurement validity.

F. General Comments

A scientifically acceptable asbestos exposure measurement should be both "reliable" and "valid," but both reliability and validity have several different aspects. Reliability can refer to the repeatability of measurements across personnel, physical situations, or time. Validity can refer to the strength of the relationship either between the measurements and an established criterion, or between the measurements and a correlate of the criterion. If there is no established criterion that can be used to estimate the "predictive" validity of measurements, then it may be possible to estimate the "construct" validity of measurements by observing the strength of the relationship between the measurements and other variables which are empirically or theoretically related to the criterion.

Given certain assumptions, the data analyzed for this report could be interpreted as giving preliminary indications of the reliability and validity of the asbestos exposure algorithm, but further study is needed. In their recent report, Patton et al. (1980) addressed the inter-rater consistency or

reliability of the algorithm scores, but the authors did not address the intra-rater consistency of the scores. This latter reliability dimension could be studied by asking the same raters to survey the same sites twice.

Some of the data analyzed for this report could be used to address the algorithm's reliability in different physical situations, but it would have to be assumed that inter-rater and intra-rater measurement errors were low on the average. It would also have to be assumed that the buildings in certain areas are similar or dissimilar. Some of the data analyzed for this report could be used to address the algorithm's construct validity, but it would have to be assumed that the various dependent variables employed are related to the criterion of interest--truly representative time-weighted airborne asbestos measurements.

There are sufficiently consistent algorithm variable distributions, algorithm variable intercorrelations, and score-algorithm variable correlations across datasets to be guardedly optimistic about the reliability of the algorithm in different physical situations. It is possible that inter-rater reliability could be improved by more rigorous training methods. It is also possible that the algorithm's intra-rater reliability could be quite acceptable, but again, no data are available.

There are sufficient inconsistencies across data sets (in the relationships between the score, the algorithm variables, and various possible correlates of truly representative time-weighted airborne asbestos measurements) that it is difficult to be optimistic concerning the validity of the algorithm as it was originally proposed and used. Nevertheless, there are sufficient consistencies across datasets to be guardedly optimistic concerning the results of additional well-designed research. This research may indicate that an acceptably valid airborne asbestos level surrogate can be developed.

REFERENCES

Berry G, and Lewinsohn HC. 1979. Dose-response relationship for asbestos-related disease: implications for hygiene standards. Part I. Morbidity. Annals NY Acad Sciences, 330:185-194.

Henderson VL, and Enterline PE. 1979. Asbestos exposure: factors associated with excess cancer and respiratory disease mortality. Annals NY Acad Sciences, 330:117-126.

Logue E. 1980 (Mar. 20). Center for Health Studies, Research Triangle Institute, Research Triangle Park, NC. Similarity of Sebastien's asbestos air levels in buildings data and the data included in Nicholson's report to NIEHS. Memorandum to Cindy Stroup, Task Manager, Design and Development Branch, U.S. Environmental Protection Agency, Washington, DC.

McCrone WC; McCrone LB; and Delly JG. 1978. Polarized light microscopy. Ann Arbor, Michigan: Ann Arbor Science.

McDonald JC, and Liddell FDK. 1979. Mortality in Canadian miners and millers exposed to chrysotile. Annals NY Acad Sciences, 330:1-9.

Nicholson, WJ, et al. 1975. Environmental Science Laboratory, Mt. Sinai School of Medicine, CUNY. Asbestos contamination of the air in public buildings. Research Triangle Park, North Carolina: Office of Air and Waste Management, Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency Contract 68-02-1346.

Nicholson, WJ, et al. 1978. Environmental Science Laboratory, Mt. Sinai School of Medicine, CUNY. Control of sprayed asbestos surfaces in school buildings: a feasibility study. Washington, D.C.: National Institute of Environmental Health Sciences. Contract NO1-ES-7-2113.

NIOSH. 1977. NIOSH Manual of Analytical Methods. Cincinnati, Ohio: United States Department of Health, Education, and Welfare, Public Health Service, Center for Disease Control, NIOSH.

Patton JL, Melton CW, Schmidt EW, et al. 1980. Battelle Columbus Labs. Asbestos in schools. Draft Final Report. Washington, D.C.: Office of Pesticides and Toxic Substances, U.S. Environmental Protection Agency. Contract 68-01-3858.

Schirripa, JT. 1980 (February 7). Industrial Hygienics. Huntington, New York 11743. Letter to D. Lentzen, Systems and Measurements Division, Research Triangle Institute, Research Triangle Park, NC 27709.

Schirripa JT. N.d. Airborne levels of asbestos fibers in general occupancy buildings and an estimate of carcinogenic risk. Huntington, New York: Industrial Hygienics. Draft report.

Sebastien, P, et al. 1979. Levels of asbestos air pollution in some environmental situations. Annals NY Acad Sciences, 330:40-1-415.

Stroup, C. 1980 (August). Design and Development Branch, Survey and Analysis Division, Office of Pesticides and Toxic Substances, U.S. Environmental Protection Agency, Washington, DC 20450. Letter to T Hartwell, Statistical Methodology and Analysis Center, Research Triangle Institute, Research Triangle Park, NC 27709.

USEPA. 1979a (March). U.S. Environmental Protection Agency. Asbestos-containing materials in school buildings: a guidance document, 2 Parts. Washington, D.C.: Office of Toxic Substances, USEPA. Report C00090.

USEPA. 1979b (September). U.S. Environmental Protection Agency. Asbestos exposure assessment algorithm. Draft Report. Office of Toxic Substances.

USEPA. 1980a (September). U.S. Environmental Protection Agency. Identifying potential asbestos exposures in schools: the Montgomery County experience. Washington, DC: Office of Toxic Substances. EPA 560/13-80-039.

USEPA. 1980b (June). U.S. Environmental Protection Agency. Technical support documentation for regulatory action against friable asbestos-containing materials in school buildings. Washington, DC: Office of Toxic Substances, USEPA.

USOSHA. 1972. Permissible exposure to airborne concentrations of asbestos fibers. 29CFR1910.93a. 37 FR 110.

Appendix A

Components of the Potential Exposure Score

Appendix A

Components of the Potential Exposure Score

Factor	Range or Extent
1. Material Condition (Deterioration/Damage)	None (0) Moderate; small areas (2) Widespread; severe; pieces dislodged (5)
2. Water Damage	None (0) Minor (1) Moderate to major (2)
3. Exposed Surface Area	Not exposed. Locate above suspended ceiling. None visible without removing panels or ceiling sections. (0) 10% or less are exposed (1) 10% to 100% area exposed (4)
4. Accessibility	Not accessible (0) Low: Rarely accessible (1) Moderate to High: Access may be frequent (4)
5. Activity and Movement	None or low: Libraries, most classrooms (0) Moderate: Some classrooms, corridors (1) High: Some corridors and cafeterias, all gymnasiums (2)
6. Air Plenum or Direct Air Stream	None (0) Present (1)
7. Asbestos Content (total % present)	Trace to 1% (0) >1% to 50% (2) >50% to 100% (3)
8. Friability	Low friability. Difficult but possible to damage by hand (1) Moderate friability. Fairly easy to dislodge and crush. (2) Highly friable, fluffy, spongy, flaking pieces hanging. (3)

Preceding page blank

Potential Exposure Score Calculation

Factor		Code	
1.	Material Condition	_____	(0, 2, 5)
2.	Water Damage	_____	(0, 1, 2)
3.	Exposed Surface	_____	(0, 1, 4)
4.	Accessibility	_____	(0, 1, 4)
5.	Activity and Movement	_____	(0, 1, 2)
6.	Air Plenum	_____	(0, 1)
	SUM [1+2+3+4+5+6]	= _____	
7.	% Content	_____	(0, 2, 3)
8.	Friability	_____	(1, 2, 3)
	PRODUCT [7 x 8]	= _____	

EXPOSURE NUMBER = PRODUCT X SUM = _____